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Intelligent Driving Assistant based on Road Accident Risk Map Analysis and Vehicle Telemetry

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MASTER THESIS

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Barranquilla, Atlántico, Colombia
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A dissertation presented to the Universidad del Norte in partial fulfillment of the requirements for the degree of MASTER OF SCIENCE

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ABSTRACT

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The study presented below proposes the development of an intelligent driver assistant based on vehicle telemetry and road accident risk map analysis, whose responsibility is to alert the driver as the driving process is carried out in order to avoid risky situations that may cause traffic accidents. The on-board intelligent assistant will reproduce real-time visual-audio alerts according to information obtained from both sources (vehicle telemetry and road accident risk map), and the driving tests for development and evaluation will be obtained using a real car in a real environment. As a result, a proposed intelligent assistance agent based on fuzzy reasoning was obtained which supports the driver correctly in real-time according to the telemetry data, the road type and the principles of secure driving and transportation regulation laws.

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PART I
INTRODUCTION AND RELATED WORK

Chapter 1

Introduction

Chapter 1 provides an introduction to the work presented in this thesis. Specifically, the motivation in the research area, the pursued aims and the main contributions are briefly described. Finally, the chapter concludes with an overview of the structure and contents of the thesis.

1.1. Motivation

Currently, road traffic accidents are one of the main causes of mortality according to the statistics of World Health Organization (WHO). Over 1.2 million people die each year on the world's roads, with millions more sustaining serious injuries and living with long-term adverse consequences. Being the ninth cause of death worldwide and the main for those young-adult victims between 15 and 29 years old. It is estimated that by 2030 it may even be the seventh cause of mortality. In Colombia, about 8.000 people are victims of these accidents, including drivers, passengers and pedestrians (World Health Organization (WHO), 2015).

The main reasons for such accidents to occur are health problems, the driver skill, speeding, careless driving, and also the education and awareness of individuals who deliberately drive under the influence of alcohol or psychoactive substances (drug-driving). With these alarming statistics it is important to propose solutions in order to reduce the high accident rate and promote a responsible behavior at the time of driving. These solutions will undoubtedly lead to a significant decrease in the number of fatalities.

Over the decades, the automotive industry has made a great effort to enrich what is the experience of traveling by road. This effort has focused on improving the comfort and safety of passengers (Fuchs, Lamprecht, & Bellino, 2007).

Today, the scientific community has taken the initiative in developing vehicular measurement devices, as well as tools that seek to assess driver performance. The aim is to establish all possible causes that lead to these accidents. Scientific research has mainly converged on the following topics (Cuervo, 2013):

- Evaluation of vehicle's mechanical performance.
- Methods to detect erroneous driving behaviors.
- Audiovisual records for the analysis of behavior in driving.
- Mathematical models of driver behavior.
- Erratic driving assessment.
- Vehicle telemetry systems.
- Traffic congestion analysis.

Many road accidents occur due to lack of driver's attention or concentration while operating the vehicle (careless driving). Some drivers tend to entertain themselves with distracting activities; others find it difficult to stay focused on driving due to fatigue or health problems. Usually, elderly drivers may exhibit difficulties in personal mobility (UK Department of Transport, 2010).

Likewise, reckless driving (or dangerous) is another major fault to traffic laws, it is normally considered a more serious violation than careless driving and is commonly penalized with fines, imprisonment and / or suspension or revocation of the driver's license. Reckless driving can be defined as a mental state in which the driver performs an indifferent and meaningless behavior towards the traffic laws, frequently the driver misjudges common driving situations and procedures that can result in traffic accidents (Jain, Abhishek & Pawar, 2014).

Considering the importance of driver behavior, is it possible to develop an intelligent system that advises the driver in carelessness moments during the driving process?

In the current research, the development of an intelligent driving assistant based on vehicular telemetry and accident risk maps analysis is proposed, whose aim is to alert the driver by providing information about his practice and suggesting possible actions while the driving process is carried out, thus avoiding careless situations that may cause traffic accidents.

1.2. Objectives

This work focuses on the development of an Intelligent Driving Assistant implemented by a proposed Fuzzy Logic algorithm. The approach of the algorithm includes knowledge about Vehicle Telemetry (vehicle variables) and Road Accident Risk Maps in order to assist the driver, detecting potentially risky driving maneuvers.

- **Problem**: An integrated vehicular system that deploys intelligent driving assistance, allowing register and analyze data about the motion state of the vehicle, road accident risk map and driver's actions.
- **General Objective**: Develop a real-time driving assistance system based on an intelligent agent (implemented by soft computing techniques) according to the analysis of vehicular telemetry and road accident risk map data.
- **Goals:**
  - ✓ Characterize and analyze the most relevant variables related to driver assistance systems.
  - ✓ Adapt a vehicular telemetry system with "black box" capabilities which records the previously characterized variables of interest.
  - ✓ Study and integrate the road accident risk map analysis.
  - ✓ Design and implement an intelligent assistant that uses the acquired data, vehicle telemetry and road accident risk map analysis, to analyze the maneuvers and alert the driver during the driving process.

- ✓ Evaluate the performance of the implemented system in several study cases.

1.2.1. Thesis Question

The main question addressed in this dissertation is:

Could a system that uses computational intelligence based on both sources of information (vehicle telemetry and road accident risk map) provide driving advice under real conditions in careless moments during the driving process?

1.2.2. Approach

In this research is proposed the design of a low-cost Intelligent Driving Assistant System based on road accident risk map analysis and vehicular telemetry, which will be responsible for providing alerts and warnings to advise the driver during the journey in the moments of carelessness or inattention. This approach incorporates a driving assessment capable to identify risky maneuvers performed by the driver according to traffic regulation laws and standardized practices of safety driving.

Vehicle telemetry data acquisition is an indispensable step before driving analysis. This allows observing the behavior of each monitored signal and identifying the relationship between these variables and the maneuver performed by the driver. At the same time, the road accident risk map analysis allows to estimate the risk level of each road, so that it is possible to identify which roads are more dangerous than others.

Such monitored variables and road accident analysis can be adapted to different test scenarios, so that depending on the type of route it can set different criteria for the analysis. Additionally, the proposal seeks to apply and translate the expert knowledge of traffic laws and safe driving practices in order to achieve a driving assistance implementing intelligent computational techniques.

Finally, tests are performed by a real vehicle in a real environment, acquiring real-time signals and performing the analysis during the driving process. Thus, while the driver is on board, the intelligent assistant system is assessing point to point the performance of the monitored information. This analysis would be supported by a video record inside the vehicle at the same time the tests are performed.

1.3. Contributions

Through the application of intelligent systems in driver assistance systems, the experience of traveling by road has become much more comfortable and safe (Kannan, Thangavelu & Kalivaradhan, 2010). These are in constant development and their inclusion in the market is increasing (Riches, 2013). So, this is the added value to continue this line of research.

It is expected that, in the future, as new technologies emerge, these auxiliary schemes will continue in process of improvement and that most commercial cars will have such intelligent driving assistance systems implemented.

This thesis makes the following contributions to intelligent driving assistants:

- *Intelligent approach of a driving assistant applying soft-computing techniques, capable of emitting visual and hearing alerts using different evaluation criteria, data related to driving maneuvers through signals referred to vehicle movement (speed, longitudinal acceleration, Yaw angle rate), and data from a road accident risk map. The proposed intelligent assistant considers both sources of information for detecting dangerous maneuvers while driving.*
- *To the assistance process, it develops a computational tool capable of providing real-time assistance which is adaptable to different driving scenarios.*
- *To society, through this intelligent assistant it is expected to raise awareness and promote responsible behavior when performing the driving process.*

1.4. Reader's Guide to the Thesis

Following, it is presented a general description of the contents of this dissertation. This master thesis is organized in three main parts distributed by chapters.

Part I: Introduction and Related Works

Chapter 1 presents a motivational introduction on the main topics, objectives and contributions regarding this dissertation.

Chapter 2 gives a general overview of background information regarding transport regulation, vehicle telemetry information, road safety analysis, computational intelligence and intelligent transportation systems, necessary to develop the proposed approach described in chapter 4 and 5.

Chapter 3 provides a general survey of the most relevant work related to the research addressed in this thesis.

Part II: Proposed Approach

Chapter 4 describes the formal aspects of the intelligent driving assistant approach presented in this thesis.

Chapter 5 presents the implementation of the approach proposed in chapter 4. The chapter also contributes to complete the description of such proposal.

Part III: Results and Conclusions

Chapter 6 provides experimental results of the implemented approach. An experiment design is presented to evaluate the performance of different criteria that evidence the utility, pertinence and feasibility of the overall approach.

Chapter 7 discusses and analyzes the results, summarizes the conclusions and contributions of the thesis and outlines the most promising directions for future work.

Chapter 2

Background Information

This chapter introduces and reviews general concepts of transportation regulations, vehicle telemetry information, road accident risk analysis, computational intelligent systems and intelligent transportation systems required for developing the proposed approach.

2.1. Vehicle Telemetry Information

2.1.1. Global Positioning System (GPS)

The Global Positioning System (GPS) is a global navigation system developed by the United States Department of Defense (USDOD). Currently, this system is comprised by 24 artificial satellites in orbit with their respective ground stations, providing information for positioning 24 hours a day no matter the weather conditions (Casanova, 2002). It is fully operational since 1995. The GPS consist mainly of two parts:

- First, the artificial constellation of twenty-four (24) satellites previously mentioned (21 regular and 3 backup), orbiting around the earth and called NAVSTAR (Navigation Satellite Timing and Ranging). These are located in six orbital planes, each consisting of four (4) satellites, and are used as a reference point for calculating positions on the earth surface (Fig. 2.1.2-1).

- Second, the GPS receivers, which are responsible for these calculations according to the data received from four (4) satellites or more. The receiver estimates its position by trilateration, with a few meters of error. It is also responsible for storing the position and time data to measure travel time and speed, in case it is required to locate an object in motion.

Although the GPS service was developed for purely military purposes, it allows public access in a degraded version and less precision of the signals emitted by the satellites. It is designed so that anytime and anywhere of the planet there are a least four (4) satellites in line of sight and the calculations are almost instantaneous, allowing its application to any type of vehicles regardless of its movement speed.

2.1.2. GPS Receiver Communication – NMEA Standard

The National Marine Electronics Association (NMEA) has developed a standard to permit ready and satisfactory data communication between electronic marine instruments (navigation and communication equipment used in maritime navigation). GPS receiver communication is defined within this specification too.

This standard is intended to support one-way serial data transmission from a single “talker” to one or more “listeners”. This is data in printable ASCII format and may include information such as position, speed, depth, frequency allocation, etc. The idea of NMEA is to send a line of data called a sentence (or message) that is totally self-contained and independent from other sentences. Typical messages might be 11 to a maximum of 79 characters in length and are organized in several data fields separated by commas. Generally, require transmissions no more often than one message per second (NMEA 0183, 2002).

The first of these data fields is the header, and it defines the interpretation of the rest of the sentence. Whatever device or program that reads the header can watch for the data sentences of interest and ignore the other ones. In NMEA standard there are no commands to indicate that the GPS receiver should do something different, and there is no way to indicate anything back to the transmitter unit as to whether the sentence is being read correctly or to request a re-send of some data that could not be obtained. Instead, the receiver unit checks the checksum and ignores the data if the checksum verification is failed (Mehaffey, Yeazel, Penrod & Deiss, n.d.).

Crucial data from GPS receiver are sent by the sentence NMEA RMC (Recommend Minimum sentence C), which format is shown below:

`$GPRMC,123519,A,4807.038,N,01131.000,E,022.4,084.4,230394,003.1,W*6A`[1]

Where:

- $GP: Beginning characters of the sentence.
- RMC: Recommend Minimum sentence C.
- 123519: Data taken at 12:35 UTC (Coordinated Universal Time).
- A: Device status (A = active or V = void).
- 4807.038,N: Latitude in decimal degrees, North.
- 01131.000,E: Longitude in decimal degrees, East.
- 022.4: Speed over the ground in knots.
- 084.4: Track angle in degrees True (Heading).
- 230394: Date – 23rd of March 1994.
- 003.1,W: Magnetic Variation.
- *6A: The checksum data, always begins with *.

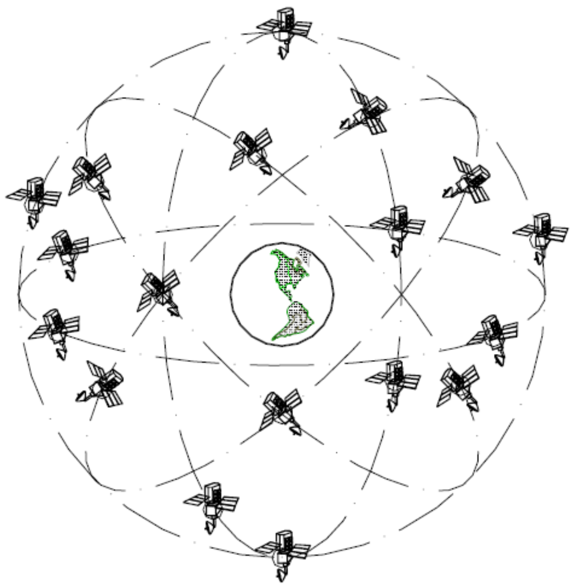


Fig. 2.1.2-1 – Graphic representation of the artificial satellite system NAVSTAR (Casanova, 2002)

2.1.3.Video Camera Recording

Another technique widely used by road safety systems are the employ of video cameras on board the vehicle. These can be applied either to monitor the driver himself, in order to determine any unusual behavior, as well as the vehicle environment, in order to detect proximity to neighboring objects (vehicles, pedestrians and infrastructure elements) or improper car outlets in its lane. In general, this field covers any application based on information coming from the capture of images, and so the results obtained in these studies are strongly influenced by the light conditions of the target to record (vehicles side, driver's head, road demarcation, road signs, nearby vehicles, pedestrians, etc.).

2.2. Road Accident Risk Analysis

One of the basic objectives of road accident data analysis is to identify the main problems in the field of road safety. The collected data should be analyzed and reviewed to find locations with safety issues or high accident risk, in order to apply countermeasures that improve safety. The efficiency in the prevention of accidents depends significantly on the reliability of the collected data and the use of the appropriate methods of analysis.

According to the United States Department of Transportation (USDOT) through the Federal Highway Administration (FHWA), there are several types of data analysis that can be conducted to support road safety depending on the available data (crash, road and exposure data) (United States Department of Transportation (USDOT), 2011). Some of them are:

2.2.1. Crash Frequency

This is one of the simplest ways to analyze accident data. It is defined as the number of accidents occurred within a specific time and place (territory, road segment or intersection). Multiple accidents occurring at the same location over a period of time may be an indication of a safety issue or a zone with high accident risk.

2.2.2. Crash Averaging

As the accidents are relatively sporadic events, it is important that a safety analysis includes an adequate time interval of study. Using Crash Averaging it is possible to normalize crash data over a longer period of time (over one year) to look for annual anomalies that can alter other analyses. Due to the randomness of traffic accidents, it is very probably that any year could have a much higher or lower number of accidents than its previous or later one. A rule of thumb is to collect data from the previous 3 to 5 years, with 3 years as a minimum.

2.2.3. Trend Analysis

Another form of analysis is to examine the trend of accidents over time, to determine if there has been an increase or decrease in the number of accidents. An increment may indicate an emerging accident risk. It is possible to organize the accident history into categories indicating both the number of accidents and the later trend.

2.2.4. Crash Rates

Crash Rate analysis takes into account exposure data and gives a relative measure of the accident risk level in a road segment or intersection. This is calculated to determine relative safety compared to other similar roads and usually uses exposure data in the form of traffic volumes or roadway mileage.

Regularly, traffic volumes are expressed in terms of Annual Daily Traffic (ADT). However, the traffic volume data is not always available at the jurisdiction level of interest (zone, road, road segment, intersection, etc.). In these cases, rates can be calculated using other exposure data, such as roadway length. This information may be obtained from the State agencies.

The advantage of using crash rate analysis is that it provides a more effective comparison between similar locations with high accident risk. This helps at the moment of setting priorities in these locations when considering safety improvements with limited resources. Among the used rates there are:

- Road Segment Rate

Eq. 1 shows the formula to calculate the road segment rate:

$$R = \frac{100.000.000 * C}{365 * N * V * L} \tag{1}$$

Where:

- R: Accident rate of the road segment given as accidents per 100 million vehicle-miles of travel (VMT).

- C: Total number of accidents of the road segment in the period of study.
- N: Number of years of data.
- V: Traffic volume (or traffic flow). Number of vehicles per day in both directions.
- L: Length of the road segment in miles.

- Intersection Rate

To calculate the intersection rate, it is used the Eq. 2:

$$R = \frac{1.000.000 * C}{365 * N * V} \tag{2}$$

Where:

- R: Accident rate of the road intersection given as accidents per million entering vehicles (MEV).
- C: Total number of intersection accidents in the period of study.
- N: Number of years of data.
- V: Daily traffic flow entering the intersection. Number of incoming vehicles per day.

- Crash Rate by Roadway Mileage

When the traffic volume data is not available, another way to compare roads is through its lengths (Eq. 3). It provides a comparison more accurate than the simple crash frequency:

$$R = \frac{C}{N * L} \tag{3}$$

Where:

- R: Accidents per mile of the road segment given as accidents per each 1 mile of roadway per year.

- C: Total number of accidents of the road segment in the period of study.
- N: Number of years of data.
- L: Length of the road segment in miles.

The correct way to use any accident rate is as a relative measure to determine which road, segment or intersection is safer than the others. The method consists on calculating an average accident rate for the road network and use it as a benchmark for the comparison. At the same time, this average can be used to compare the road safety with other local road networks.

2.3. Computational Intelligent System

According to Gottfredson, L., intelligence is defined as a very general capability that involves the ability to reason, plan, adapt, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience (Gottfredson, 1997) (Legg & Hutter, 2007). Others define it as the degree to which an entity or a system approximates and applies a certain level of knowledge to solving problems (Newel, 1994). Or also, it can be understood as "the facet of mind underlying the human capacity to think, to solve novel problems, to reason and to have knowledge of the world" (Legg & Hutter, 2007). On the other hand, a system can be defined as a set of elements (devices or artificial objects) organized in a logical and orderly way that work in harmony to achieve a specific goal.

With this in mind, a computational intelligent system is one capable of providing solutions to complex problems that conventional methods cannot solve. These systems comprise abilities of planning, reasoning, learning, evolution and adaptation to develop programs with some level of intelligence. In general, for a computer system to be considered intelligent, it must meet at least one of the following characteristics:

- Learning: able to acquire knowledge or skills through experience, study or by teaching. This requires that the system has memory to store the learning.

- Reasoning: able to think about something in a logical way.
- Adaptation: able to adjust to the problem conditions.
- Evolution: related to learning, able to improve its work thanks to the learning process.
- Autonomous: able to take decisions by itself or accept help if necessary.

The operating principle of the computational intelligent systems is to develop a processing system that takes the information (raw data) and gives it a meaning, i.e., that generates knowledge. In this way, the level of abstraction is increased until the expertise is reached. It should be noted that these expert systems are used as a decision support, they do not seek to completely eliminate the human being intervention. So that they do not necessarily force a decision but give a recommendation.

Very important to clarify that because a system is intelligent it does not mean that it cannot be wrong, but it should minimize the number of errors.

Fuzzy logic is a generalization of boolean logic. While boolean logic is deterministic, where there are only two possible logical levels of membership one (1) or zero (0) (yes or no), in fuzzy logic there could be multiple levels of membership whose values are assigned between zero and one. In this way, a certain range of values can be part of several sets at once and not just one at a time. This association called degree of membership is established through the membership functions, whose forms determine how much a value belongs to a set (Ross, 2010).

The operating mode of the fuzzy system begins by assigning a group of fuzzy sets to a variable domain, so that the punctual values of the variable are not used but the labels of the assigned sets. This process is called *fuzzifying*. Such fuzzy variables come into association through a set of compositional rules of inference (CRI or just fuzzy inference rules), where the expert knowledge of the intelligent system is reflected. The result of this association are new fuzzy variables and the final step is to perform the reverse process of the beginning, the fuzzy labels are interpreted to extract the desired punctual values. This process is called *defuzzifying*, which consists on adding the final results of each rule (according to the values assigned to each input) and obtain the new value by the centroid of the total (standard method). The complexity of this technique is to approximate the expert knowledge through the fuzzy inference rules and the fuzzy sets of the input and output variables.

To develop the present approach, it is use a structured inference engine based on fuzzy logic for two main reasons:

- Easily adaptable to the evaluation criteria used to identify properly driving behaviors according to the Traffic Regulation Laws and Road Accident analysis.
- Is the one that most resembles human behavior because that is how the human being reasons. Decision making based on fuzzy knowledge.

2.4. Intelligent Transportation Systems (ITSs)

Since its first appearance and over the years, transport vehicles have been a matter of study and research in multiple areas of knowledge to become today into highly technological elements. Electronics and sensory devices were incorporated into these vehicles as intelligent driver support systems.

The current research is developed within the field of Intelligent Transportation Systems (ITS). Meaning ITS all those systems in which information and communication technologies are applied in the area of road transport, including infrastructure, vehicles, users, and also the field of traffic and mobility management (European Union, 2010).

The so-called Driver Assistance Systems (DAS) have been developed in order to support the driver in his duty to guide the vehicle for its own safety and comfort. These assistance systems are responsible for multiple tasks and maneuvers (Fürer, 2011). Previously, such tasks were performed independently, each one with their respective sensory devices (radars, cameras, ultrasonic sensors, among others). The objective is to carry them out in the most satisfactory and efficient way possible, so as to reduce the work load carried by the driver (Verband der Automobilindustrie (VDA), 2015).

The broad field of artificial intelligence provides multiple concepts and methods for the development of Intelligent Systems (IS), which fit very well in this work environment (Fuchs, Lamprecht & Bellino, 2007). Currently, thanks to advances in computer systems and intelligent systems, it has been possible to develop more capable, robust and integrated driver assistance systems (I-DAS Intelligent Driver Assistance Systems or ADAS Advanced Driver Assistance Systems) (Fuchs et al., 2007) (VDA, 2015), able to perform more complex tasks, with better control, in which a certain level of reasoning is needed for proper planning and decision making. Such systems are able to detect, analyze, predict and react according to the characteristics and information collected about the status of the vehicle and its environment (Kannan et. al, 2010).

Current technology in driver support systems is very diverse in terms of functionality, methodology and implementation. Some of these very practical systems are already available in the market, to mention Blind-Spot detectors, Lane change assistants and Back-up/Parking sensors for example, others more elaborated are still in process of development and study (Jain, Abhishek & Pawar, 2014).

As an example of these complex systems, there are research works where an integrated and highly exhaustive approach is developed, as can be seen in the study made by Jiménez, F., et al. (Jiménez, Naranjo, Anaya, García, Ponz & Armingol, 2016). The approach proposed in this study is the development of an integrated driving assistance system for inter-urban environments, in order to improve safety and efficiency through the implementation of a set of specific applications. This set of applications makes up a cooperative system whose information source is based on: A perception system on board the vehicle and a communication system between vehicles and infrastructure (V2V and V2I). So, the first one provides all direct information of the environment and the second one complements the first in cases where the first presents difficulties, thus expanding the scope of perception. In addition, the proposed system also has vehicle automation (speed and steering control) being able to perform autonomous maneuvers in case a dangerous situation is detected and the driver does not act properly. The cooperative system consists of: An Adaptive Cruise Control (ACC), an Overtaking Assistance System, an Intersection Assistance System and a Collision Avoidance System.

Although we have seen that there is a great variety of fields of study in ITS, where the assistance systems are developed, today most academic research in driving support systems focuses more on automating the driving process rather than on the actual driver's awareness (Jain, Abhishek & Pawar, 2014). While it is true that the deployment of technologies in the automation process effectively prevents or contributes to the decrement of traffic accidents, this effectiveness could not be achieved if the drivers did not understand what exactly safe driving is. So, the consciousness state of the driver is very important even with the deployment of the ITSs (Kazuaki, Masaki & Katsuya, 2012). In other words, in addition to the technical optimization of the vehicle, road safety can also be increased by optimizing the driver behavior (Yay & Martínez, 2013).

Chapter 3

Related Work

This chapter presents an overview of the main works focused on the topics addressed in this dissertation.

3.1. Traffic Accidents as a Matter of Study

As previously mentioned, nowadays road traffic accidents are one of the main causes of mortality around the world according to WHO, comprising around 1.2 million victims per year with other millions suffering injuries as a consequence of them. In an attempt to reduce the numbers or at least mitigate the severity, several government institutions and agencies in charge of traffic management have carried out statistical studies in order to identify all those factors involved in these accidents.

In general terms, these works require time and, depending on the scope, handling huge amounts of data. Because of that, the most common is to find road accident studies for a certain region or sector. The main objective of these studies is to identify all those factors that cause road traffic accidents and analyze the relationship between them, since traffic accidents usually do not occur because of a single cause.

A clear example of these works is the accident analysis made by Wade, M., et al. In this report, an extensive statistical study of traffic accidents on roads with low traffic flow is carried out. The proposed analysis is divided into three (3) sections:

the first focuses only in identifying the factors that may cause these accidents; the second in identifying which roadways have the highest accident rates; and the third, in determining which are the most significant factors involved in these accidents. For the first part, the parameter used is the accident frequency, so that the behavior over time of said accidents is studied regarding different factors (weather conditions, road surface conditions, etc.) and classifying them according to their characteristics such as, injury severity, driver age, among others. For the second part, accident rates are used to identify the roads with highest accident risk and also specify which points of the road are the most dangerous. Accident rates by number of roads, type of roads and locations are used. Finally, based on the results obtained in the previous sections, in the third one, the most influential factors in traffic accidents are determined (Minnesota Department of Transportation (MnDOT), 2004).

Following the same concept, a similar study is carried out by Al-Khateeb, G., where a statistical analysis of traffic accidents is also performed. Likewise, the objective in this work is to identify the causes that lead to traffic accidents and their relationship with the behavior of the driver, pedestrians, and other actors involved. In the same way, the parameters used for this study are accident frequency and rates, organizing and classifying accidents according to characteristics such as: injury level, fatality, weather conditions, pavement conditions, light conditions, driver type, speed limit, age group, among others (Al-Khateeb, 2010).

It should be noted that most of this type of works corresponds more to the area of civil engineering. These are studies with a purely informative focus and are crucial for decision making when proposing and implementing viable solutions, this in order to decrease the number of road accidents.

3.2. Telemetry Data and In-Vehicle Data Acquisition Systems

There are assistance systems that focus on those variables that can be taken directly from the vehicle, such as the variation of Yaw angle, pedaling, steering, speed, accelerations, engine conditions, among others. In many cases, these telemetry systems exhibit black box properties (Cuervo, 2013), and depending on how they have been implemented, they could be acquisition systems designed specifically for a particular vehicle, like OBD (On Board Diagnostics) systems, or standard systems (flexible telemetry devices) which can be used for different vehicles. In general terms, the typical structure of these systems consists of a sensor network distributed throughout the vehicle. In this grid, each element acquires its respective data to send it to a central processing point on the vehicle (CPU or microcontroller on board). From this point, it is possible to perform any desired processing scheme to the information obtained.

As an example, there are researches where the focus of study is just the basic control of the speed limit allowed (Johari, 2008). Here, Johari, A., et al. developed a system that informs the driver when the speed limit has been exceeded, avoiding a large proportion of collision risks.

On the other hand, there are assistance systems based on the real-time tracking of vehicle's position. Khan, A., et al. develops an on-board economic tracking system based on a GPS receiver and a GSM (Global System for Mobile Communications) communication module, both connected to a microcontroller. The GPS receiver constantly supplies the vehicle’s location to the micro and the GSM module sends a message with this data to the monitoring station whenever it requests it. Thus, a taxi station, for example, can have control over the position of their vehicles and the places where they have been (Khan & Mishra, 2012). Another similar application is developed by Singh, J., et al. where a prototype tracking system based on GSM / GPS is also used for real-time monitoring of ambulances, in this case the objective is, through the ambulance’s location and a traffic density controller, assist the ambulance to use the less congested route to the point of the accident and then to the nearest hospital (Singh, Rajendra & Swetha, 2015).

However, vehicle telemetry systems can not only acquire information about the vehicle’s motion state, but also about its environment, thus allowing the development of perception systems. Ya-Wen, H., et al. presents the development of an intelligent road detection system composed by a webcam, a laser range finder, an Inertial Measurement Unit (IMU) and a Real-time Kinematics Differential Global Positioning System (RTK-DGPS), all devices on board a golf cart. In this study, the webcam, laser range finder and IMU (image processing, distance and acceleration information respectively) were integrated with the purpose of detect potholes and construct a roadway quality analysis system, by then, based on the GPS information (latitude and longitude), expose the results on Google Maps. In this work, the multisensory integration of the detection devices allows to compensate the limitations of each device separately (Ya-Wen, Jau-Woei & Zong-Han, 2016).

3.3. Digital Image Processing in Driving Environments

At the same time, another branch of the driving assistance systems seeks to provide support through the use of video cameras. This field covers all those assistance systems based on capture, image processing analysis and advanced computer vision algorithms. While it is true that video cameras can also be part of the vehicle telemetry systems previously mentioned, the treatment of images involves a much more complex work, being able to provide more information than other devices. Obstacle detection, proximity between vehicles and pattern recognition like road signs are some of the study points.

To illustrate, Bounini, F., et al. presents a robust road boundaries and painted lines detection system which is used to keep intelligent and autonomous vehicles on the road during the trip. This work focuses in developing an accurate and efficient algorithm that seeks to eliminate the constrains of real-time road lanes detection, this due to the large amount of data that must be processed. The proposed approach suggests that of each captured frame of the front camera, what really matters is not the whole frame, but only the sector that contains the roadway. So that reducing the area of each frame to only the region of interest (ROI), the amount of data that needs to be processed decreases considerably. This detection system is developed along with a dynamic vehicle control system in the Pro-Sivic simulation environment (Bounini, Gingras, Lapointe & Pollart, 2015).

As well, there are assistance systems capable of detecting the level of drowsiness that the driver has. Surendra, M. et al. proposed a model to recognize driver drowsiness by means of a continuous observation of the eyes through video cameras, in order to detect when the driver's eye is closed or open. In this way, it is possible to issue warnings (alarms) with enough time and then decrease the speed of the vehicle (Surendra, Bhavana, Pooja & Ashish, 2015). Likewise, Prajapati, N., et al. propose a system capable of detecting drowsiness not only through the continuous observation of the eyes but also the mouth and nose, so that identify yawning actions (Prajapati & Bhatt, 2016).

More elaborated works seek to complement this approach including not just visual features of the driver but non-visual and behavior features. Bagus, G., et al. discuss the design of systems that in addition to detect drowsiness by facial patterns, detect drowsiness by patterns emerged from human body like heartbeat, brain wave, blinking and skin. In this case, it is necessary implement other special sensors attached to driver´s body (Bagus, Igi & Teguh, 2017).

As we can see, implementations with video analysis have been important and satisfactory results have been obtained. Other studies like of Yang, Y., et al. focus on the detection and classification of traffic sings instead of drowsiness or road lines (Yang, Luo, Xu & Wu, 2016).

3.4. Driving Modeling and Driver Behavior Analysis

To realize intelligent driving assistance, driver behavior analysis and modeling are also important challenges. The prediction and recognition of driving patterns are some of the points to be addressed in this type of studies.

In this sense, there are works that focus on the study of driver behavior in different types or sections of roads. More specifically, Zhao, M., et al. analyze human driver behavior in interaction with roundabouts. In this study it is develop an efficient method to predict whether a vehicle, having entered a roundabout, will choose the upcoming exit or stay at the roundabout. Based on the information obtained from a field study of human drivers interacting with roundabouts (steering wheel angle and angle velocity), they implement a support vector machine (SVM) as a classification method for the recognition problem of roundabout leaving/staying patterns. In this way they managed to predict the behavior of the driver in this situation with a high level of accuracy (Zhao, Käthner, Jipp, Söffker & Lemmer, 2017).

There are also studies that seek a more custom character on driver assistance systems. As Rakhshan, A., et al., where they indicate that, although the accident warning systems contribute in reducing collisions or at least their severity, most of these systems are developed based on the data of a given population and not on the individual characteristics of each driver, so that in many cases drivers may perceive false alarms. In this study, a new approach that seeks to estimate in real-time the distribution (statistical behavior) of Brake Response Time (BRT) of the current driver is developed, using data obtained from a Vehicular Ad-Hoc Network (VANET) and based on this estimation, the system adjusts alert algorithms according to the individual characteristics of each driver (Rakhshan, Ray & Pishro-Nik, 2014).

Other works like Cuervo, A., et al., considers the problem of diagnosing people's driving skills under real conditions using GPS data and video record. In this work, an intelligent driving diagnosis system based on the records of vehicular telemetry data is implemented. The system consists of an intelligent diagnosis agent able to assess the driving process with the same criteria that an expert human driver would use. This expert agent abstracts knowledge of some traffic laws and some secure driving techniques implemented in a set of fuzzy rules. According to the telemetry data (GPS signals) and the criteria reflected in these fuzzy rules, the proposed system allows diagnosing different types of drivers in different type of routes and provides a quantitative assessment of driving performance with high degree of reliability (Cuervo, Quintero & Premachandra, 2014). Regarding this study, the present work shares the same approach of analyzing the vehicle motion state by means of a GPS-based telemetry system (vehicle telemetry). In the same way, it seeks to develop an intelligent agent based on fuzzy reasoning. However, the road accident risk map analysis (vehicle environment) is now added to this approach, which was not considered in the previous work. In addition, the new goal is to provide feedback to the driver in real time by issuing driving suggestions according to a set of risk maneuvers (assistance). Unlike Cuervo, A., et. al, where only a global quantitative evaluation of the driving process is provided (diagnosis).

3.5. Towards to an Intelligent Driving Assistant

Nowadays, the inclusion of intelligent assistants in the automotive industry is notorious and imminent. As Lugano, G. points out, while on the one hand the scientific community is still debating the purpose that artificial intelligence has within the driving process, the automotive industry has already launched to market products and services based on these intelligent systems. The intelligent driving assistants already commercially available, according to its design and functionality, follow two trends: those that consist of just integrating intelligent assistants originally designed for smartphones and tablets to vehicles, and the others that seek to develop own specific assistance systems for the driving environment. Some examples of the first trend are found "Google Assistant", adopted by Mercedes-Benz and Hyundai; "Cortana" (Microsoft) adopted by BMW and Nissan; and "Alexa" (Amazon) adopted by Ford, whose role focuses only in navigation and entertainment assistance. Examples of the second trend are found "Yui", developed by Toyota; "HANA" by Honda; and "Sedric" by Volkswagen, which are still in a concept stage and it is estimated that their assistance does not only cover navigation and entertainment, but also other topics (virtual companion) that contribute to improving vehicle safety (Lugano, 2017).

However, while the term driving assistant is very broad and ambiguous, due to the diversity of active and passive applications that essentially manage to assist the driver and therefore deserve to be called assistants, the current research emphasizes the concept of an expert advisor assistant which accompanies the driver during the journey, providing recommendations to improve driving in real time.

With this in mind, Yay, E., et al, developed an intelligent driving assistant called SEEDrive, whose main objective is to optimize the driver behavior regarding areas of energy efficiency and road safety. The assistant acquires information from the car, the driver and the environment using an in-car serial bus system to be processed later by a fuzzy inference engine, thus analyses the driving behavior and gives adequate recommendations to the driver. Additionally, the system adapts itself to the individual driving behavior and predicts the vehicle state, allowing the generation of alerts in real time and adjusting the assistant to the driver needs to increase its acceptance. For this work, the authors start from the premise that beside the technical optimization of the vehicle (sensors, control units, etc.), energy efficiency and road safety can be improved as well by optimizing the driver behavior (Yay & Martínez, 2013).

In the same way, a web-based supervisor assistant called Assistant System for Safe Driving by Informative Supervision and Training (ASSIST) is developed by Kazuaki, G., et al., which allows a safe driving manager, who is out of the vehicle, to educate the driver at distance while the driving process is carried out in real time. ASSIST is composed by two subsystems, an on-board system and a supervision system outside the vehicle. The first one collects the driver behavior data from the sensorial network of the vehicle in a central computer, to send it later to the second one through a wireless communication module and internet. The assistance provided focuses on collision avoidance according to the relationship between the vehicle motion state, the headway distance and the breaking distance. Already with the data in the supervision system, it is possible to perform assistance (education) by a manager in real time or record the information for later analysis (Kazuaki, Masaki & Katsuya, 2012).

On the other hand, it is important to note that intelligent systems applied in real vehicles have been motivated thanks to the positive results obtained from the simulators. In this sense, Quintero, C., et al., presents an intelligent driving assistant based on artificial neural networks (ANNs), capable of emitting reliable driving recommendations when risky maneuvers are detected for improving driving performance, this according to the data obtained from an accident risk map analysis and an intelligent driving diagnosis. The proposed system was developed in the Racer Car Simulation platform and results emphasize the suitable functionality of the system and the impact of reducing the accident risk by using the assistant. So, a next stage would be the implementation of the system in a real environment (Quintero & Cuervo, 2017).

In this sense, the present work seeks to develop the same conceptual approach but implemented in a real vehicle. In consequence, the same topics are treated, but now with a number of difficulties not present in the simulation environment. In general terms, in the case of the vehicle telemetry system, not all vehicle variables supplied by the simulator are available in real environment (vehicle movement). Therefore, the number of maneuvers that can be detected is reduced as well as the number of assists that can be issued. On the other hand, in the case of the road accident risk map, a considerable amount of driving samples is needed to develop the risk maps of the simulator test tracks. In real conditions, real data (accident reports) provided by competent institutions are needed to build such maps, which are also not always available. And then, despite having obtained positive results by implementing ANNs, the same problem arises regarding the intelligent agent. A considerable amount of data (drivers) is needed to train the network. which is a limitation in real environment (drivers availability). This, together with the previous works, motivates the development of the intelligent agent implementing other soft-computing techniques as fuzzy reasoning.

3.6. Final Remarks

The problem of maneuvers assessment and driver assistance have huge importance in ITS Research Society. With this in mind, it is necessary to establish a structured Intelligent Assistant which combines both, computational intelligence techniques and expert criteria about driving faculties, rules and safety.

As we have seen, the works mentioned above deal with different types of data related to both, vehicle movement and driver behavior. This as a consequence of the close relationship between these features and the vehicle maneuvers. The applications developed in these works focused on: satellite tracking, vehicular environment detection, driver behavior classification, driving diagnosis, secure telemetry data transmission and remote driving supervision. But it is not presented an implementation of a computational expert agent for intelligent driving assistance analysis regarding road accident risk in real environment.

This dissertation presents an Intelligent Driving Assistant approach which evaluates the vehicle motion state in order to assess driver maneuvers, through the implementation of a soft computing technique. The proposed system comprises on-board telemetry data, road accident risk map analysis and an abstraction of driving regulation laws and driving secure techniques for a real-time intelligent driving assistance. The analysis parameters will change according to the current scenario characteristics being adaptable for different study cases.

PART II

PROPOSED APPROACH

Chapter 4

Intelligent Driving Assistant Approach

This chapter presents the intelligent driving assistant approach proposed in this dissertation applied to real environment driving scenarios. The main definitions, general considerations, development stages, driving assistance and expected results are introduced in this chapter.

4.1. Problem Statement

As mentioned earlier, worldwide more than one million people are victims of traffic accidents among drivers, passengers and pedestrians. Among the most common causes that lead to these unfortunate events there are: health problems, driver skills, driver awareness (education), drug-driving and of course the road conditions (Section 1.1). Due to this, in order to mitigate the number of accidents, several governments have taken preventive measures implementing traffic regulation laws that consider these risk factors. However, these laws are not enough to cover all the risks caused by bad driving practices. With this in mind, around the world the scientific community and the automotive industry have focused their efforts on improving the comfort and safety of the actors involved in the road environment (Fuchs, Lamprecht, & Bellino, 2007).

Because that in many occasions the possibility of avoiding an accident resides in the driver, over the years, intelligent driving systems have been created. These systems help the driver to avoid collisions, get oriented and increase the efficiency in fuel consumption, hoping to improve safety on the roads (European Field Operational Test (euroFOT), 2012).

Currently, the Intelligent Transportation Systems Society (ITSS) has focused all issues related to vehicle safety assistance towards two trends: driving automation and driver's awareness. In the first one, the objective of these systems is to eliminate, either partially or completely, the intervention of the driver, while in the second one, the objective is to support the driver in terms of knowledge and alertness. For this reason, there are important studies carried out on different fields of ITSs, among those previously mentioned: vehicle telemetry signals monitoring (Cuervo, 2013)(Khan & Mishra, 2012)(Singh et al., 2015)(Yan-Wen et al., 2016), digital image processing (Bounini et al., n. d.)(Surendra et al., 2015)(Prajapati & Bhatt, 2016)(Bagus et al., 2017)(Yang et al., 2016), driving modeling and driver behavior analysis (Cuervo et al., 2014)(Rakhshan et al., 2014)(Zhao et al., 2017), and onboard assistance systems (Yay & Martinez, 2013) (Kazuaki et al., 2012) (Quintero & Cuervo, 2017).

While it has been seen that the exposed driving assistants seek to monitor the driver behavior through his actions and maneuvers, which are directly related to the signals obtained from the motion state of the vehicle and its surroundings, the development of an expert intelligent agent that carries out such assessment, and in turn provides driving recommendations according also to the degree of road accident risk, has not been proposed.

In this way, the proposed intelligent system will use vehicle motion information referred directly to the actions (maneuvers) made by de driver during the driving process. This motion information is characterized by speed, acceleration, orientation and satellite location, along with the data obtained from the road accident risk analysis. The resulting assistant will be able to provide driving suggestions evaluating potentially risky maneuvers. The development of a vehicular intelligent system, based on an expert agent dedicated to assessing the driving process in real conditions, is an important study to raise new research proposals related to this issue. This work could allow different entities such as transport companies, driving schools, transit authorities, car rental houses, among others, to be aware about driver's performance and how this may prevent road traffic accidents.

4.2. Proposed Intelligent Driving Assistant

The implementation in a real environment of an intelligent driving assistant seeks to achieve an assistance based on a proposed intelligent agent that attempts to support the driver in real-time. This approach takes into account the expert knowledge abstraction of driving laws and secure driving techniques, along with the data related to vehicle motion state and surroundings obtained from both sources of information, telemetry and road accident risk map.

In order to meet this objective, first it is necessary to establish in an orderly way the structure of the system, to present formally the assistant proposed in this work. Along with this, the properties and characteristics of each element that conforms the intelligent assistant are also described. Fig. 4.2-1 shows the formal design of the proposed approach. It is possible to identify the different sections that make up and generally summarize the solution to the problem of study in this scheme.

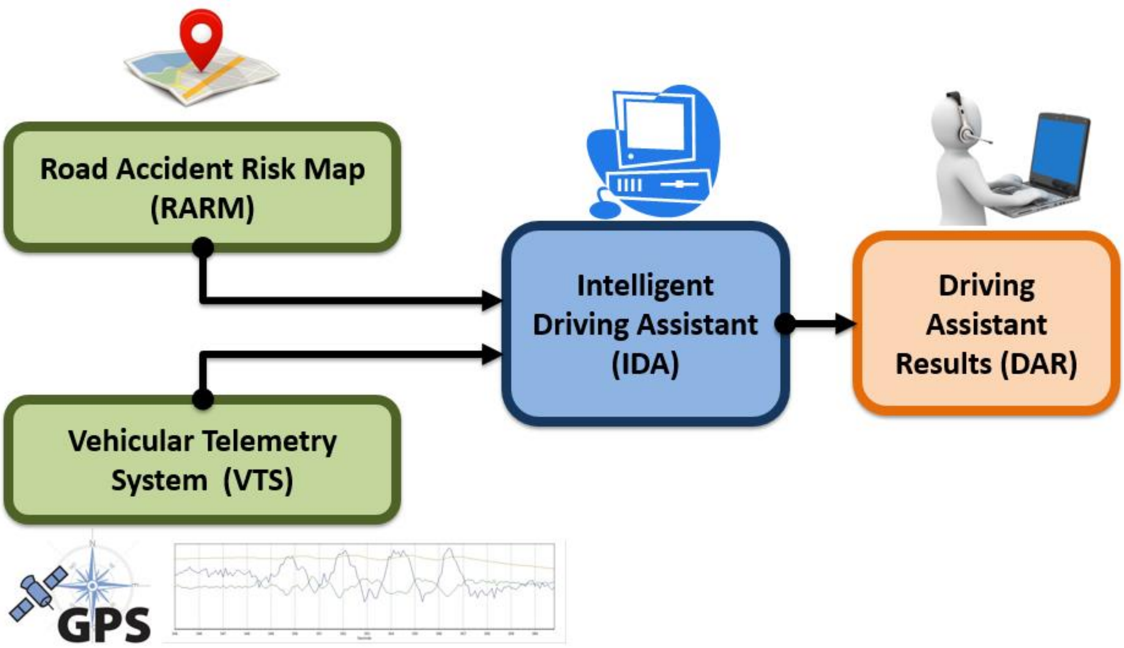
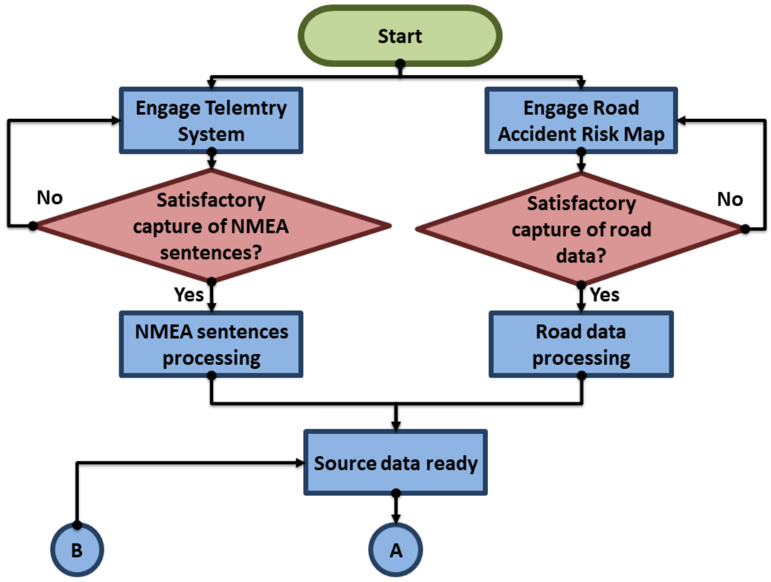
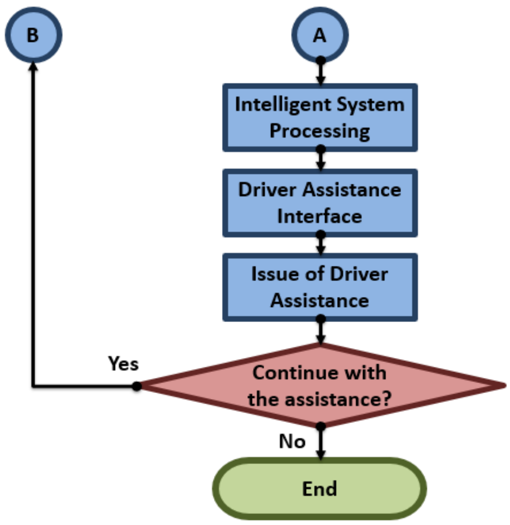


Fig. 4.2-1 - Intelligent Driving Assistant – System Scheme

Based on Fig. 4.2-1, Fig. 4.2-2 shows the flowchart of the proposed system. It presents the execution of the intelligent driving assistant, beginning with the acquisition (extraction and manipulation) of data from the vehicular telemetry and the road accident risk analysis, then, once the information is ready, the processing of this data made by the intelligent assistant, where the expert driving agent is located, and finally the emission of the visual-audio assistance.



(a)



(b)

Fig. 4.2-2 - Intelligent Driving Assistant – Flowchart

As can be seen in Fig. 4.2-1, the four sections that compose the system are: 4.2.1 Vehicular Telemetry System (VTS), 4.2.2 Road Accident Risk Map (RARM), 4.2.3 Intelligent Driving Assistant (IDA) and 4.2.4 Driving Assistant Results (DAR).

4.2.1. Vehicular Telemetry System (VTS)

The vehicular telemetry system consists of an electronic device with “black box” capabilities, easily adaptable to any car. This one is responsible for monitoring variables related to the vehicle movement (driver maneuvers), and also, recording both the interior and exterior of the vehicle through video cameras to supervise the driving process. The data acquired from the VTS follows the GPS standard protocol (NMEA standard, Section 2.1.2), so it is necessary to develop an acquisition stage for extraction and manipulation of such data (signals). When the signals are acquired, they are continuously processed by the computational system on board the vehicle to provide real-time assistance. At the same time, these data are stored to allow post-driving analysis as well.

Even though there are many maneuvers that can be carried out during the driving process, in the current work it is desired to detect three (3) risky maneuvers specifically:

- *Speeding*: as its name suggests, the first of the maneuvers to detect from the vehicle motion state is whether there is velocity excess or not. As stated by the World Health Organization, this aspect is of crucial importance due to, according to statistical studies, as average traffic speed increases, so too does the probability of an accident. If an accident occurs, the risk of death and serious injury is greater at higher speeds (WHO, 2015).
- *Bad Pedaling*: understood by the incorrect handling of pedals (throttle and brake), with which the driver has control over the vehicle longitudinal movement (forward and backward).

- *Bad Steering*: understood by the incorrect handling of the steering shaft (also known as steering column), with which the driver has control over the vehicle lateral movement (orientation).

To perform the detection of these maneuvers it is necessary to make a "variables characterization", in order to identify which signals provided by the VTS allow identifying or perceiving the mentioned maneuvers. This process is described in detail in Chapter 5.

4.2.2. Road Accident Risk Map (RARM)

The assistant raised in this work, besides using data from the vehicular telemetry system, additionally incorporates the use of "Accident Maps" as a tool that provides information about the risk level of the road (Section 2.2).

Depending on the environment where the assistant is developed, these maps can be obtained or elaborated in different ways. Generally, the risk maps are statistically constructed, taking into account the number of errors (accidents) committed by drivers in a specific area or road. For this, it is necessary to establish the criteria by which the accident map will be made. According to the manual "Road Safety Information Analysis" (USDOT, 2011), it is known that there are different parameters to analyze the road accident degree according to the available information. Thanks to this accident degree, it is possible to identify which roads present greater risk than others. In the current case, as it is desired to implement the driving assistant in a real environment, the map is created using a database based on the number of traffic accidents reported by road in a given period of time. This type of information can be obtained from state agencies or institutions involved in the management of traffic flow.

The development of a driving assistant based on RARMs, seeks to study the influence of such risk in the evaluation of driving maneuvers, along with the telemetry variables previously described.

Studies carried out by different institutions show that a higher speed, there is a greater probability of road accidents to occur (WHO, 2015). However, this does not imply that speeding is a bad driving practice all the time, since there are roads specially designed to drive at high speeds and these do not necessarily present the highest accident rate. In the same way, the acceleration and steering maneuvers are strongly related to the speed of the vehicle, due to what can be considered an aggressive steering maneuver at high speed, to low speed it is not. This same concept, attached to the risk of accidents, implies that for a road with a low degree of accident, there would be no problem in committing maneuvers with a certain level of risk.

This flexibility, when detecting and evaluating risk maneuvers, is one of the main objectives looked for in the development of the current intelligent driving assistant.

4.2.3. Intelligent Driving Assistant (IDA)

The proposal of the exposed intelligent driving assistant approach focuses on presenting the properties and characteristics of the intelligent agent in charge of assessing the driver maneuvers. This IDA seeks to detect dangerous maneuvers in a given time.

For this, it is necessary to take into account two important aspects in the development of the intelligent assistant. The first one, consist on the signals (variables) that are taken from the vehicle and its environment, which must be directly related to the driver actions and therefore are essential to study the current motion state of the vehicle. And the second one is related to how possible it is to approximate the knowledge of an expert driver in an intelligent computational agent, so that it carries out the evaluation in terms of safety and risky maneuvers.

In consequence, this section has been divided into three stages that make up the intelligent assistant:

- Data acquisition: In this stage, the data acquisition from the two previously mentioned sources of information (vehicular telemetry and road accident risk map) is carried out. A previous processing is made to extract and organize the data (variables of interest); and also, the parameters used in the evaluation of driving maneuvers are established. These parameters (evaluation criteria), related to the variables of interest, are constantly adjusted according to the type of road in which the intelligent assistant is found, allowing to perform tests in different roads and study cases.

- Expert driving knowledge: This stage contains the design of the proposed intelligent agent, which comprises an abstraction of the knowledge based on traffic regulation laws and secure driving principles. This abstraction is represented by a set of qualitative driving rules that an experienced driver would accomplish. The developed intelligent agent seeks to approximate the same assessment that an expert driver would make about driving maneuvers.
- Data and knowledge integration: The final stage of the intelligent assistant combines the previous two stages. In this case, the expert knowledge embodied in the second stage is applied to the signals acquired on the first stage, i.e., the intelligent agent processes the acquired data and performs the assessment of maneuvers according to the evaluation parameters and the established driving rules.

In order to meet this goal, a fuzzy inference system is implemented. This due to the previously mentioned advantages provided by this soft-computing technique (Section 2.3 and 3.5): easily adaptable evaluation criteria, similarity to human reasoning and drivers availability.

4.2.4. Driving Assistant Results (DAR)

With this work it is expected to develop an intelligent assistant capable of issuing driving tips to reduce the risk of accidents and support drivers in careless moments. In the same way, it is desired to create awareness for inexperienced drivers and for those who perform dangerous maneuvers even knowing that it is wrong. More specifically, it is expected that the assistant issues driving recommendations for each risky maneuver previously indicated (Section 4.2.1).

The assistant performance will be evaluated according to three (3) points of interest. The first one concerning the proper functionality of the system, that is, that the system works coherently and manages to detect risky maneuvers and assist the driver; the second one referring to the effectiveness of the system, in this case, how well does the assistant work; and the third one regarding the incidence of using the assistant in the driving process. For this, different routes will be carried out to evaluate the system performance in different study cases, and thanks to the post-driving analysis and video recording it will be possible to clarify or detect behaviors that might seem confusing during the journey.

4.3. Final Remarks

As seen so far, the proposed approach seeks to develop a driving assistant which collects characteristics of the previous works presented in Chapter 3. On the one hand, a vehicular telemetry system is used to obtain information of vehicle movement along with the use of video cameras to monitor the driver behavior and observe the route. On the other hand, the environment data is given by the accident risk, which is specific to each road. And finally, it seeks to approximate human expert criteria on driving process assessment through an intelligent driving assistance system, based on an intelligent agent implemented by soft-computing techniques (fuzzy logic) capable of detecting risky maneuvers and assisting the driver by emitting driving advises to improve safety.

Once formally presented the conceptual design of the desired assistant, below in Chapter 5 it is exposed the implementation methodology in real environment following the same structure stablished in this chapter,

As previously mentioned, the performance of the assistant will be evaluated according to its functionality and efficiency, and it is expected that the system can properly detect risky maneuvers and assist the driver.

Chapter 5

Intelligent Driving Assistant Implementation

This chapter presents the application of the proposed approach in a real environment. The adapted vehicular telemetry system, the road accident risk map and developed computational system are described along with the road assessment parameters and the driving assistant algorithm. It comprises some specific considerations about the intelligent assistant system and scenarios characteristics.

5.1. General Implementation Overview

The implementation of the proposed approach known as "Intelligent Driving Assistant based on Road Accident Risk Map Analysis and Vehicle Telemetry" is possible by hardware and software integration. The sections described in the previous chapter are treated again but from a methodological point of view. Although it is true that the thesis main objective focuses on exposing the proposed intelligent agent in charge of the assistance labor, it is also important to describe the implementation of the other elements that conform the driving assistant. Following the structure proposed in Chapter 4 (Section 4.2), first the elements responsible for supplying data are presented, then the developed computational system, and finally the intelligent assistant itself.

5.2. Adapted Vehicular Telemetry System (VTS)

5.2.1. RACELOGIC VBOX Mini

This device, based on GPS, is a high-precision performance meter used in real vehicles for competitions (automotive testing) and provides a large amount of data related to the vehicle motion state. It can work as a data logger for post-driving analysis, being able to store data on a removable SD flash card, or as a real-time performance meter, being able to stream data to an on-board computer for an in-situ analysis (RACELOGIC, 2014). Such device is adopted as the VTS (Section 4.2.1) and it is used and tested for the variables selection process (variables characterization). Fig. 5.2.1-1 shows the VBOX Mini equipment and Table 5.2.1-1 presents some features of the device.

Fig. 5.2.1-1 – Vehicular Telemetry System (VTS)

VBOX Mini
10 Hz fully calibrated GPS engine
SD or SDHC flash card (max size 2GB)
Internal and external GPS antennas
Back-lit LCD screen for viewing live data
RS-232 socket for connection to other modules
USB interface
Rugged plastic enclosure

Table 5.2.1-1 – VBOX Mini Features (RACELOGIC, 2014)

The VBOX GPS engine allows to supply data at a sampling rate of 10Hz for USB connection and 1Hz for serial connection (RS-232 socket). It can accept SD flash cards up to a maximum size of 2GB. Thanks to the external antenna it can obtain very accurate data, however it can also work using only the inbuilt (internal) antenna. Through the LCD screen live data can be observed and also it can be checked the VBOX configuration. Although it is possible to use both connection options to acquire data on the on-board computer, it is decided to work with the RS-232 connection (serial communication) at 1Hz sampling rate, because in this way the data can be transmitted to other modules in real-time without using the own VBOX software.

As mentioned earlier, the data provided by the VTS follows the NMEA standard protocol. In this case, the VBOX Mini supplies two (2) NMEA sentences in this configuration, the RMC (Recommended Minimum Sentence C) and the GGA (Global Positioning System Fix Data). The data used for the driving assessment comes from these sentences.

5.2.2. Variables Characterization

The reason why a variables study is carried out is because the aforementioned risky maneuvers (Section 4.2.1) can be detected in different ways (using different signals), especially the *Bad Steering* maneuver. The process consists on selecting which signals best perceive the established maneuvers. The signals selected to detect *Speeding*, *Bad Pedaling* and *Bad Steering* are *Speed*, *Longitudinal*

Acceleration and *Yaw Angle Rate* respectively. Following, each of them is described and it is shown how detection is perceived:

➢ *Speeding* Detection

Instants of time in which the driver exceeds the speed limit allowed in the current road, so that it can be directly perceived by observing the "speed" of the vehicle.

- *Speed* [km/h] (*SPD*): the velocity that the vehicle performs. According to WHO, speed is a critical factor for road traffic injuries. As average traffic speed increases so also does the probability of an accident. If an accident occurs, the risk of death and serious injury is greater at higher speeds (WHO, 2015). Due to this reason, many governments and agencies involved in speed management are established speed limits in order to balance road mobility and safety, as well as employed electronic devices that can detect the speed of vehicles, thus have control over the driving practices.

Fig.5.2.2-1 shows an example of how speed behaves in time.

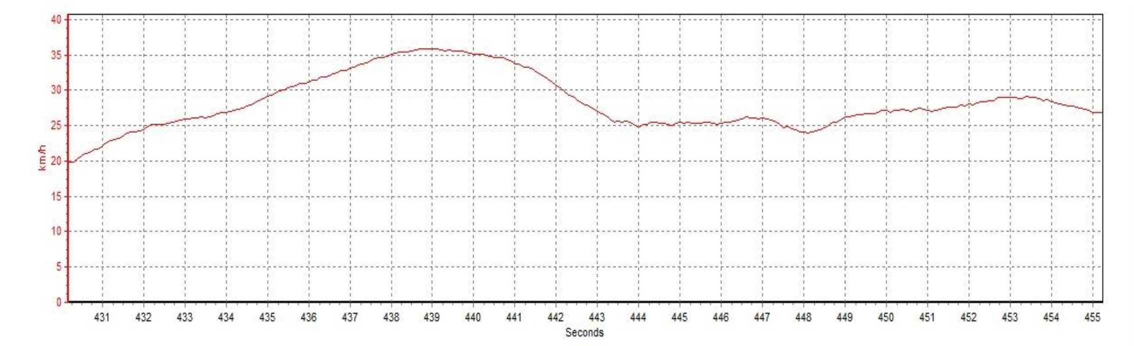


Fig. 5.2.2-1 – *Speed* [km/h] (*SPD*) signal

➢ *Bad Pedaling* Detection

It is considered an incorrect handling of pedals when driver performs abrupt or sudden acceleration or deceleration actions, so that it can be directly perceived by observing the "longitudinal acceleration" of the vehicle.

- *Longitudinal Acceleration* [G] (*LA*): it is referred to the longitudinal acceleration (increasing speed when driving towards and decreasing speed when braking) experienced by the driver and directly related to pedaling maneuvers. On this field, when talking about acceleration and driving behavior, accelerations above 0.32G are considered aggressive. Best practitioners stablished that the acceleration and braking process should be progressive over the time, this represents acceleration values between 0.1 and 0.23G in magnitude, which are considered low (Mehar, Chandra & Velmurugan, 2013). Higher values can be achieved by performing abrupt or sudden acceleration maneuvers.

Fig. 5.2.2-2 shows how longitudinal acceleration behaves in time along with speed. It can be seen that for abrupt deceleration maneuvers the longitudinal acceleration perceives such variation, whereas for gradual decelerations it does not.

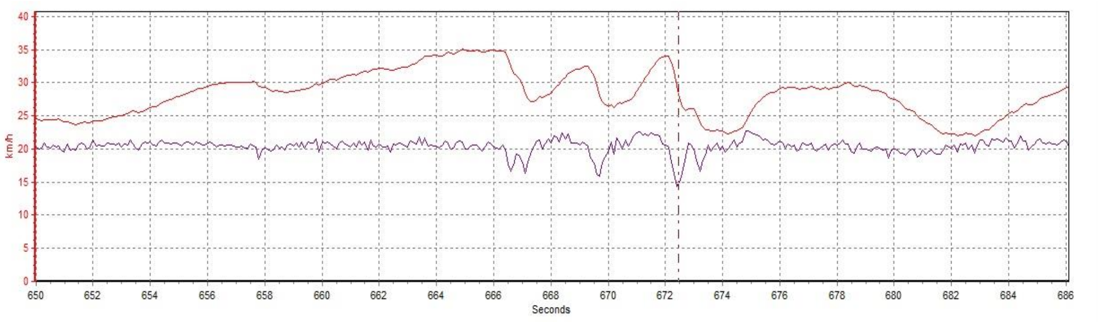


Fig. 5.2.2-2 – *Longitudinal Acceleration* [G] (*LA*, purple) and *Speed* [km/h] (*SPD*, red) signals

➢ *Bad Steering* Detection

It is considered an incorrect handling of the steering shaft when driver performs abrupt or sudden steering maneuvers (changes in vehicle orientation). In this case, the steering maneuvers (made by the steering wheel) can be perceived through three (3) different variables, so it is desired to observed which of these signals is the most sensitive to steering:

- *Heading* [°]: it describes the vehicle orientation angle respecting to the magnetic north (direction).
- *Yaw Angle Rate* [°/s] (*YAR*): it describes the vehicle orientation angle swept per second (or orientation angle rate of change).

- *Lateral Acceleration* [G]: it is referred to the acceleration (centrifugal force) experienced by the driver when performing turning maneuvers.

Due to the amplitude ranges and according to the curves showed in Fig. 5.2.2-3 and Fig. 5.2.2-4, the yaw angle rate proves to be the one that best recognizes these maneuvers.

297,323 ° < *Heading* < 305,679 ° => Amplitude Range = 8.356°

-13,297 °/s < *Yaw Angle Rate* < 16,367 °/s => Amplitude Range = 29.664 °/s

-0,352 G < *Lateral Acceleration* < 0,253 G => Amplitude Range = 0.605 G

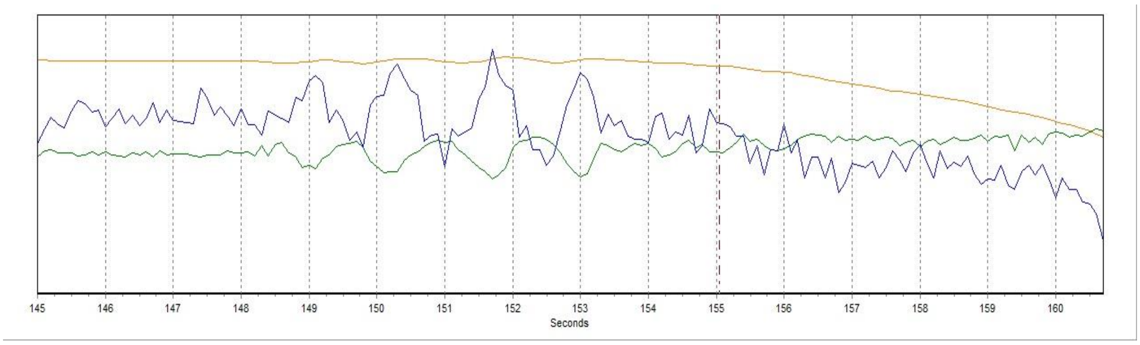


Fig. 5.2.2-3 – *Heading* [°] (orange), *Yaw Angle Rate* [°/s] (*YAR*, blue) and *Lateral Acceleration* [G] (green) signals for soft steering maneuvers

291,721 ° < *Heading* < 311,873 ° => Amplitude Range = 20.152 °

-24,201 °/s < *Yaw Angle Rate* < 22,668 °/s => Amplitude Range = 46.869 °/s

-0,524 G < *Lateral Acceleration* < 0,477 G => Amplitude Range = 1.001 G

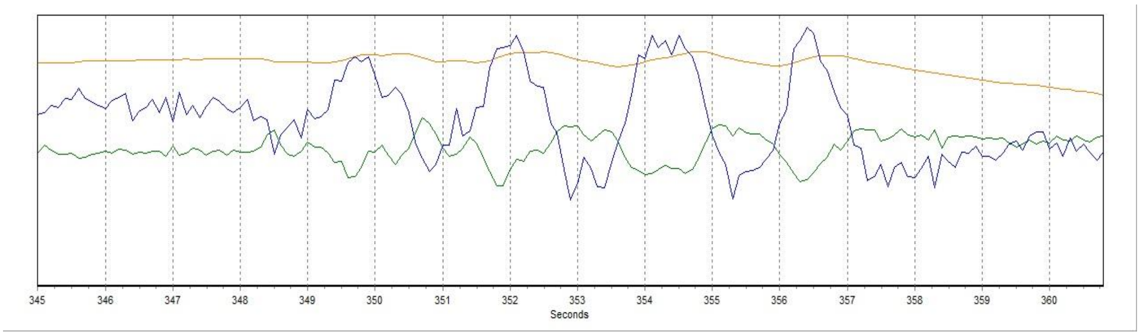


Fig. 5.2.2-4 – *Heading* [°] (orange), *Yaw Angle Rate* [°/s] (*YAR*, blue) and *Lateral Acceleration* [G] (green) signals for strong steering maneuvers

For both cases, soft and strong steering maneuvers, the yaw angle rate presented the largest range of variation, being the most sensitive signal to detect steering maneuvers. A low YAR magnitude means normal use and not dangerous driving, therefore, it is possible register a secure driving behavior. In this case, YAR values close to 30 °/s are considered sharply fluctuations (critical values) and, therefore, aggressive steering maneuvers (Liu, Liao & Rong, 2017) (Pan & Zhou, 2017).

Along with all three monitored signals, the proposed system is supported by video records of driver and road, allowing to supervise the process and eliminate any analysis that might be ambiguous or misunderstood.

5.3. Implemented Road Accident Risk Map (RARM)

As mentioned earlier, depending on the environment where the assistant is developed, there are different ways to obtain or elaborate a RARM. In the same way, there are different parameters to study the accident degree of roads according to the available information. In the current work, as it is desired to implement the driving assistant in real environment, it is decided to create a RARM using a database based on the number of traffic accidents reported by road in a given period of time (Section 4.2.2).

With this in mind and reviewing the different types of data analysis exposed in Section 2.2, it is used the Crash Rate by Roadway Mileage as assessment parameter to identify roads with high accident risk (Section 2.2.4). Taking the crash rate as the *Road Accident Risk* (RAR), Eq. 4 is gotten from Eq. 3:

$$RAR = \frac{C}{N * L} \tag{4}$$

Although the description indicates that the length of the road (L) must be in miles, it is also possible to use kilometers instead. This adjustment is in accordance with the unit system used by each country and of course, the equation allows to make such change.

The methodology to build the RARM consists first in calculating the RAR of each road for which number of accidents (C) information is available. In this sense, the database is expanded and then implementation of this accident data is incorporated in the driving assistant.

For the accident data implementation and finally build the RARM, the concept of "tags" is used to classify the roads. According to its functions and characteristics, the roads can be classified into three (3) types (Alcaldía de Barranquilla Distrito Especial, Industrial y Portuario, 2012) (Ministerio de Transporte, 2011): "*Highway*", those designed for high-speed traffic flow like department or national roads; "*Urban*", those designed for deliver traffic to highways like arterial, semi-arterial or collector roads (in-city roads); and "*Local*" those designed for low-speed traffic flow like residential or school roads. . Each of them presents a set of parameters through which the intelligent assistant executes the maneuvers assessment, these will be explained in detail in Section 5.4.1. Unlike these parameters, which are constant for each type of road, the RAR parameter is constant for a specific road and thanks to this, there is a relative measure to determine which roads are riskier than others.

5.4. Developed Computational System

The computational system presented in this work comprises all three (3) sub-stages that conform the Intelligent Driving Assistant (IDA) (Section 4.2.3). It acquires data from the VTS and the RARM and allows the intelligent agent to assist the driver based on the received signals. The system is designed to assist the driving of a single driver at a time, regardless driver type, road or used vehicle. It also presents information about the driving assistance made by the intelligent agent, showing the process step by step in the software interface.

In addition, the designed computational system allows to perform two types of analysis:

- Online Analysis: when required to evaluate a driver during his driving process in real-time.
- Offline Analysis: when required to evaluate driving registers of any driver after the tests in a post-driving analysis.

In both cases, the information related to the vehicle motion state, the driver and the intelligent assistance is available from the computational system interface. Finally, by a Google Maps API request, it is possible to use geo-referencing to show the vehicle location in a map. As it was mentioned earlier, the data obtained for the intelligent assistant is acquired from NMEA sentences values at a given time at a sampling rate of 1Hz.

5.4.1. Data Acquisition and Assessment Parameters

As a result of the variable selection process (Section 5.2.2), it is already known which are the signals of interest (data) desired to extract. While the complete acquisition of the two (2) NMEA sentences provided by the VTS is performed, it is only interested to study the behavior of three (3) variables in time (see Section 5.2.1): *Speed* (*SPD*), *Longitudinal Acceleration* (*LA*) and *Yaw Angle Rate* (*YAR*).

In this sense, only *SPD* is directly extracted from the RMC sentence (Eq. 5), the others are indirectly obtained through mathematical calculations. In the case of *LA*, it comes from the variable *SPD* (Eq. 6), and in the case of *YAR*, it comes from the variable *Heading* (θ) which is also directly extracted (Eq. 7):

$$SPD = spd(t) \tag{5}$$

$$LA = la(t) = \frac{\Delta spd(t)}{\Delta t} \tag{6}$$

$$YAR = yar(t) = \frac{\Delta \theta(t)}{\Delta t} \tag{7}$$

In the same way, the rest of data related to position, height, date and time is extracted from the NMEA sentences as well.

As mentioned in Section 4.1, several governments have taken preventive measures by implementing traffic regulation laws and electronic devices in order to mitigate the number of accidents, or at least reduce their severity. These traffic laws (fixed by statistical studies and road conditions) are relevant to set evaluation criteria, necessary criteria by which the driver's proper behavior is determined. So that based on traffic regulation laws, the parameters that the intelligent agent uses to evaluate risk maneuvers are established.

Following the postulates proposed by Cuervo, A., where the proposed approach implements fuzzy logic for the design of an intelligent system responsible of driving diagnosis, in our work is decided to use the same evaluation parameters for the monitored signals processing. Eq. 8, 9 and 10 show these parameters and each one represents the maximum limit allowed for each variable (Cuervo, 2013):

$$SPD_{Norm} = \frac{spd(t)}{SPD_{limit}} \tag{8}$$

$$LA_{Norm} = \frac{la(t)}{LA_{limit}} \tag{9}$$

$$YAR_{Norm} = \frac{yar(t)}{YAR_{limit}} \tag{10}$$

Where:

- *Speed limit* (SPD_{limit}): maximum *SPD* allowed for a certain road type (Section 5.2.2). In this case, 40 km/h for *Local* roads, 60 km/h for *Urban* roads and 90 km/h for *Highways* (Section 5.3) (Ministerio de Transporte, 2011).

- *Longitudinal Acceleration limit* (LA_{limit}): maximum *LA* allowed. As previously mentioned, values between 0.1 and 0.23G in magnitude are considered progressive acceleration and braking maneuvers, while values above 0.35 are considered aggressive (critical values) (Section 5.2.2). Such critical values are never reached. So, based on field tests, it is selected a maximum *LA* for each type of road, fixing 0.23G for *Local* roads, and 0.17G for *Urban* and *Highways*.
- *Yaw Angle Rate limit* (YAR_{limit}): maximum *YAR* allowed. In the case of *YAR*, values around 30 °/s are considered abrupt steering maneuvers (critical values) (Section 5.2.2). Such critical values are never reached as well. So again, based on field tests, for this parameter it is selected a value of 27.5 °/s for *Local* roads and 21 °/s for *Urban* and *Highways*.

The main reason to employ this standardization of variables as evaluation parameters is, for feasibility issues when implementing a single intelligent assistant adaptable to different roads, instead of implementing an intelligent assistant for each road type. In this way, only by adjusting the maximum limit value for a certain road, a single adjustable assistant can be obtained.

In the case of the *RAR* (Section 5.3), as this parameter actually provides just a relative measure, it is necessary to set a standard to know when it is had a high, low or moderate accident risk. For this, this standard measure corresponds to the average of all the *RARs* of a certain sector (RAR_{avg}). This way Eq. 11 is obtained:

$$RAR_{Norm} = \frac{RAR}{RAR_{avg}} \tag{11}$$

5.4.2. Computational Interface

In order to achieve a friendly interaction between the user and the computational system, a software interface is developed; where all the information handled by the assistant is presented. Following, Fig. 5.4.2-1 shows the software interface designed for the computational system and each of the elements that make it up.

In Fig. 5.4.2-1, it is possible to observe the GPS tracking window, where the vehicle position is identified along with the telemetry signals. Here, the variables behavior over time can be graphically monitored. The same interface is used for both types of analysis. Along with the tracking and signal monitoring, there are four (4) other panels, shown in Fig 5.4.2-2, that present data of system configuration, current vehicle motion state and intelligent assistant:

- Operation Mode: This is the first panel of interest, because in this one the desired analysis type is configured. On the one hand, for "*Online Analysis*", in the character field must be entered the name of the text file (.txt) to be generated. On the other hand, for "*Offline Analysis*", a browse window is displayed to select the desired test file (.txt) to be analyzed.
- Telemetry Data: This panel shows the current numeric values of the monitored signals. Date and time of each sample; latitude, longitude and altitude for vehicle location; and then *Speed* (*SPD*), *Longitudinal Acceleration* (*LA*) and *Yaw Angle Rate* (*YAR*) signals; along with the sample number.
- Detection Parameters: Detection Parameters panel presents the features of the current road with the evaluation criteria used for the assistant, which are automatically adjusted for each road. First there are the name and type of the road following by its accident risks (also showed in a color bar to illustrate how high the risk level is), and then the evaluation criteria (maximum limit) of each variable (Section 5.4.1).
- Intelligent Assistant: The Intelligent Assistant panel indicates which assistance is been emitted. When an assistance is issued, it is presented in both ways, visually and aurally. The assistance is shaded in the panel and at the same time, the place of occurrence is marked both on the map and on the signals monitoring. Three (3) possible assistances have been established, one for each risk maneuver (Section 4.2.1): "*Slow Down*" (orange) for *Speeding*, "*Brake Slowly*" (purple) for *Bad Pedaling* and "*Soften Steering*" (cyan) for *Bad Steering*. To the right of the panel, it is recorded the number of assists emitted and then the total amount of assists is presented.

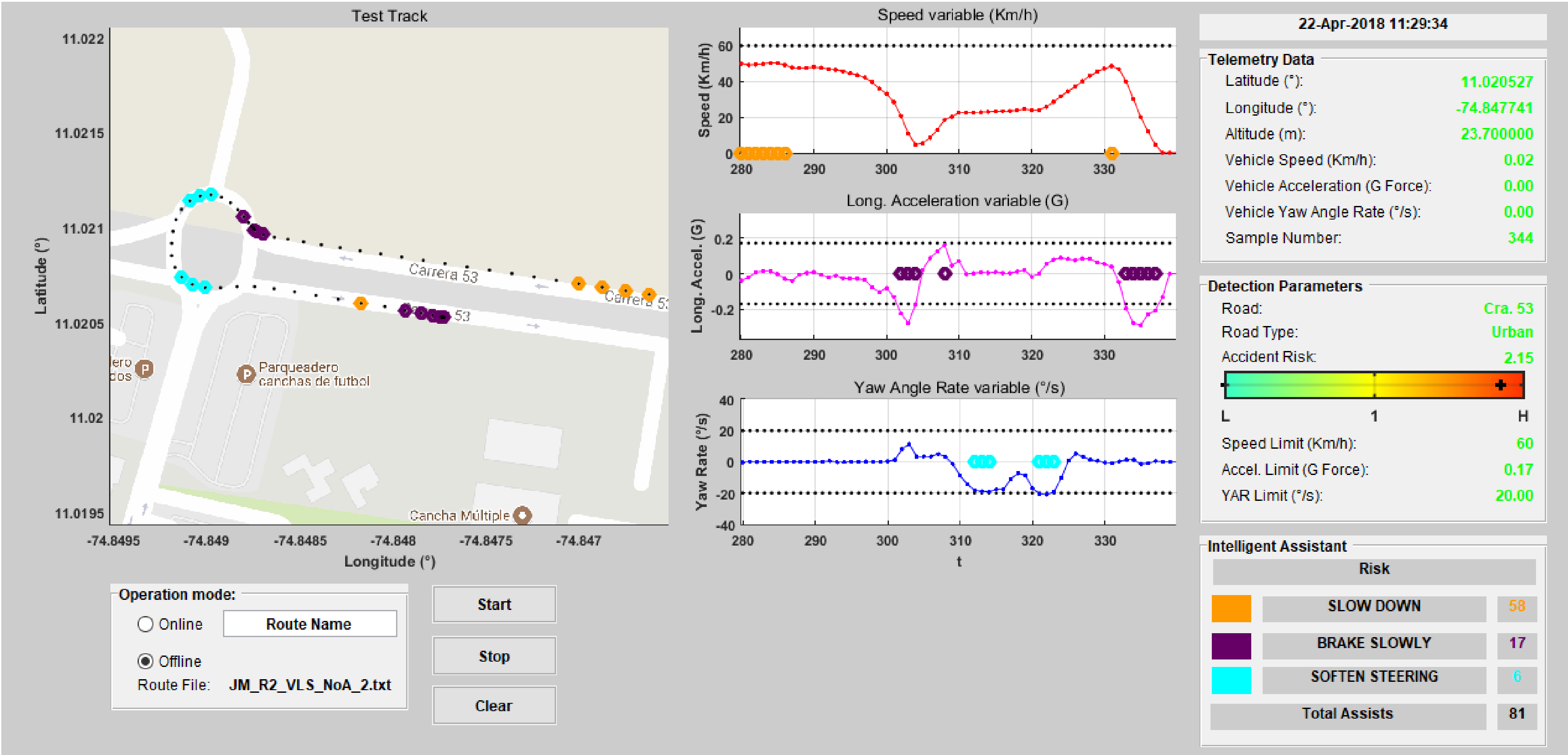


Fig. 5.4.2-1 – Software Interface for Intelligent Driving Assistant (IDA)

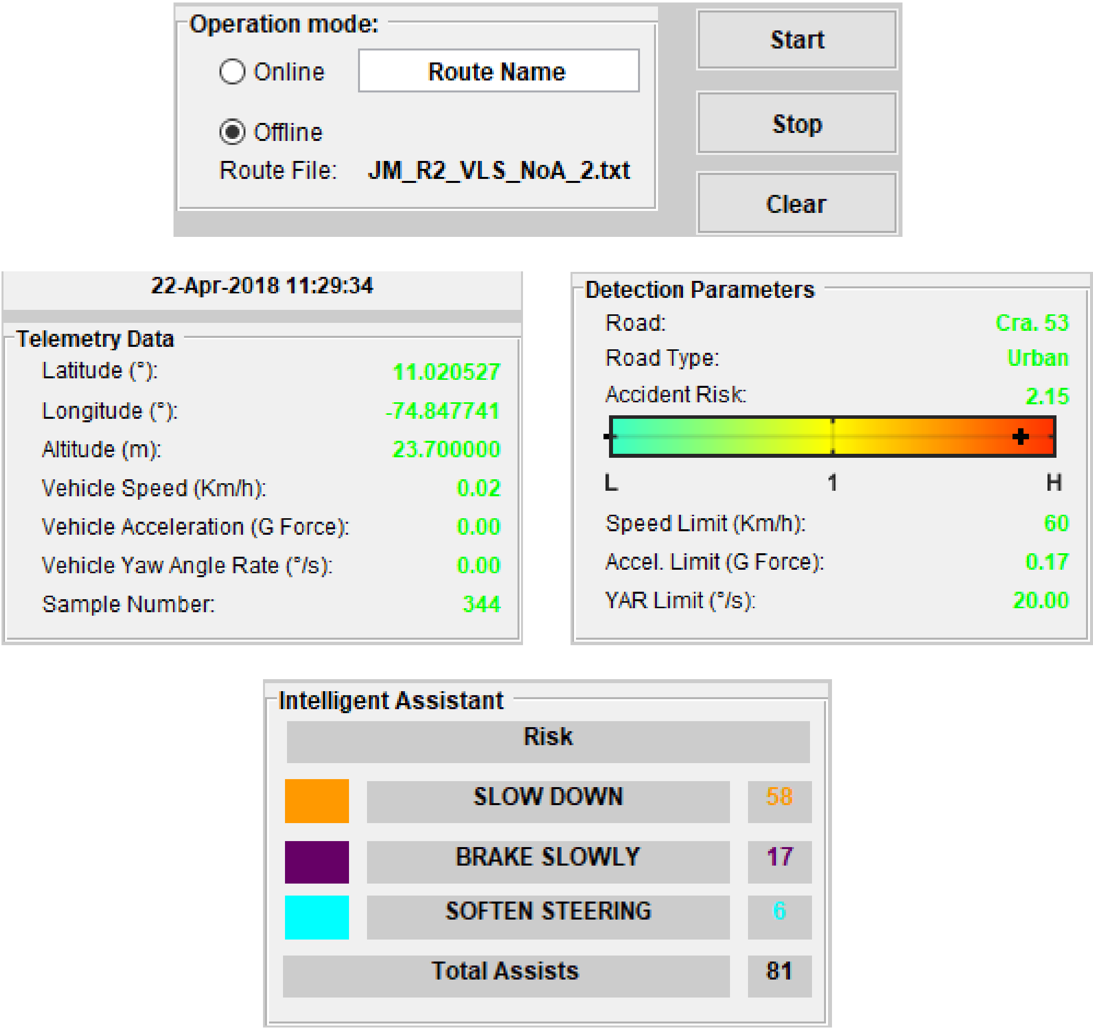


Fig. 5.4.2-2 – Software Interface Panels

5.5. Intelligent Driving Assistant (IDA) Algorithm

In this section, the proposed algorithm for the intelligent driving assistant and its properties are presented. More specifically, the two (2) remaining stages previously established (Section 4.2.3) for the development of the driving assistant are discussed.

As mentioned earlier, the proposed approach implements Fuzzy Logic (Section 2.3) for the design of an intelligent agent responsible for the task of driving assistance, that is, support the driver by emitting driving recommendations. The proposed fuzzy inference system processes all monitored signals together with the road accident risk to analyze the maneuvers made during the trip.

The abstraction of the expert knowledge based on traffic regulation laws and secure driving principles are reflected by a set of fuzzy inference rules along with the membership functions of the input and output variables. Again, what is desired is to develop an intelligent agent that approximates the same assessment that an expert driver would make about driving maneuvers.

5.5.1. System Inputs (Fuzzifying Process)

For variable analysis, the agent is based on four (4) input signals: *Speed* (*SPD*), *Longitudinal Acceleration* (*LA*), *Yaw Angle Rate* (*YAR*) and *Road Accident Risk* (*RAR*).

Following the operating mode of a fuzzy system, first comes the *fuzzifying* process, in which each input variable is assigned a group of fuzzy sets (membership functions). A function set for each variable is define as follows:

- *Normalized Speed* (SPD_{Norm}): It is described by three (3) labels, "*Low*", "*Normal*" and "*High*". Fig. 5.5.1-1 shows the membership functions set.

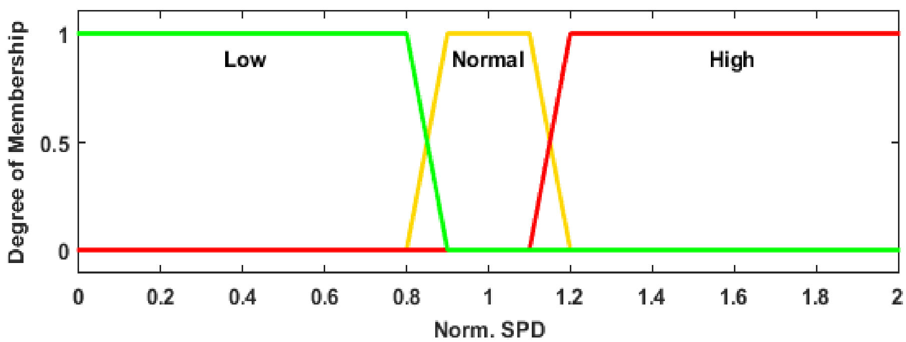


Fig. 5.5.1-1 - *Normalized Speed* (SPD_{Norm}) membership functions

- *Normalized Long. Acceleration* (LA_{Norm}): It is described by three (3) labels, "*Soft*", "*Normal*" and "*Strong*". Fig. 5.5.1-2 shows its membership functions set.

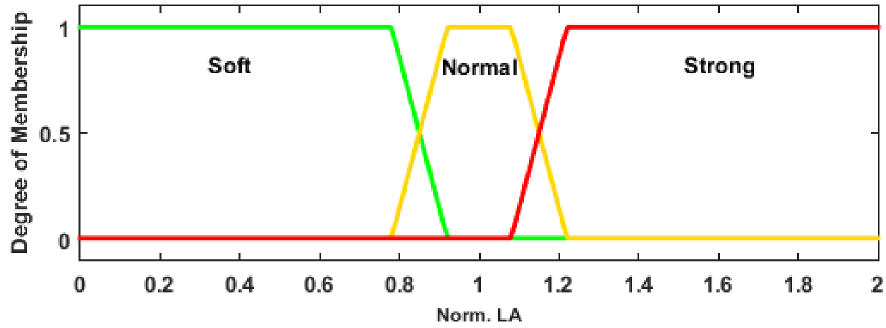


Fig. 5.5.1-2 - *Normalized Long. Acceleration* (LA_{Norm}) membership functions

- *Normalized Yaw Angle Rate* (YAR_{Norm}): It is described by two (2) labels, "*Normal*" and "*High*". Fig. 5.5.1-3 shows its membership functions set.

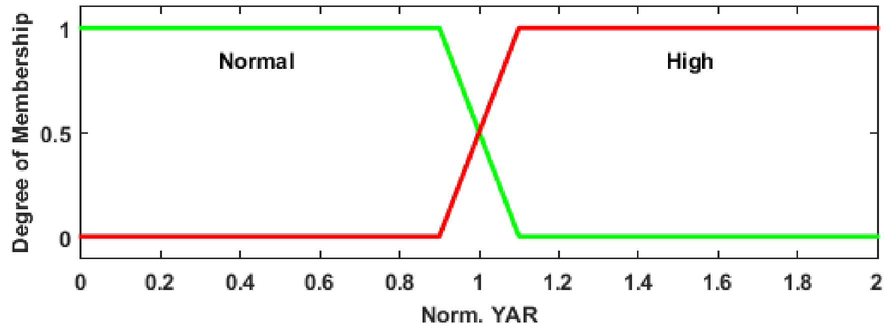


Fig. 5.5.1-3 - *Normalized Yaw Angle Rate* (YAR_{Norm}) membership functions

- *Normalized Road Accident Risk* (RAR_{Norm}): it is described by three (3) labels, "*Low*", "*Normal*" and "*High*". Fig. 5.5.1-4 shows its membership functions set.

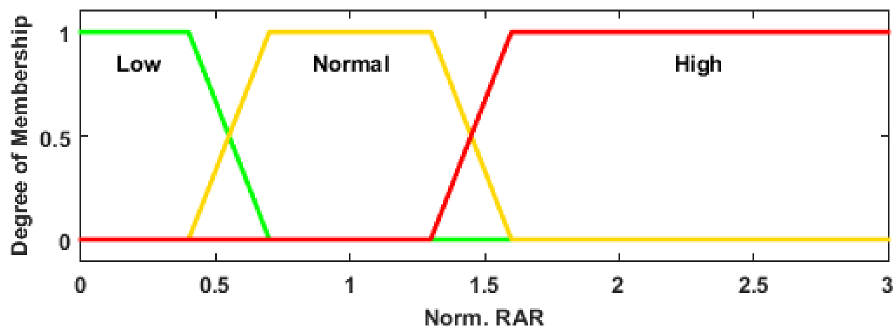


Fig. 5.5.1-4 - *Normalized Road Accident Risk* (RAR_{Norm}) membership functions

5.5.2. Fuzzy Inference Type and Rules

Then, the next step is the association of the previous fuzzy variables. Based on principles of secure driving and transportation regulation laws, a rule set for the fuzzy inference system is proposed in order to approximate the expert knowledge of safe driving for the intelligent driving assistant (see Appendix A for Rule Set Selection Process). Table 5.5.2-1 shows the proposed rule set.

Rules	Input				Output		
	SPD_{Norm}	LA_{Norm}	YAR_{Norm}	RAR_{Norm}	Speeding	Bad Pedaling	Bad Steering
1	High			Low	High		
2	High			Normal	High		
3	Normal			High	High		
4	High			High	High		
5	Low	Strong		Low		High	
6	Normal	Strong		Low		High	
7	Low	Strong		Normal		High	
8	Normal	Normal		Normal		High	
9	Normal	Strong		Normal		High	
10	Low	Normal		High		High	
11	Low	Strong		High		High	
12	Normal		High	Low			High
13	Low		High	Normal			High
14	Normal		High	Normal			High
15	Low		High	High			High

Table 5.5.2-1 – Proposed Inference Rules for Intelligent Driving Assistant (IDA)

Fig. 5.5.2-1 illustrates the variables dependency followed by the fuzzy rule set. The detection of *Speeding* relies on the values of SPD_{Norm} and RAR_{Norm}; *Bad Pedaling* on S_{Norm}, LA_{Norm} and RAR_{Norm}; and then *Bad Steering* on S_{Norm}, YAR_{Norm} and RAR_{Norm}.

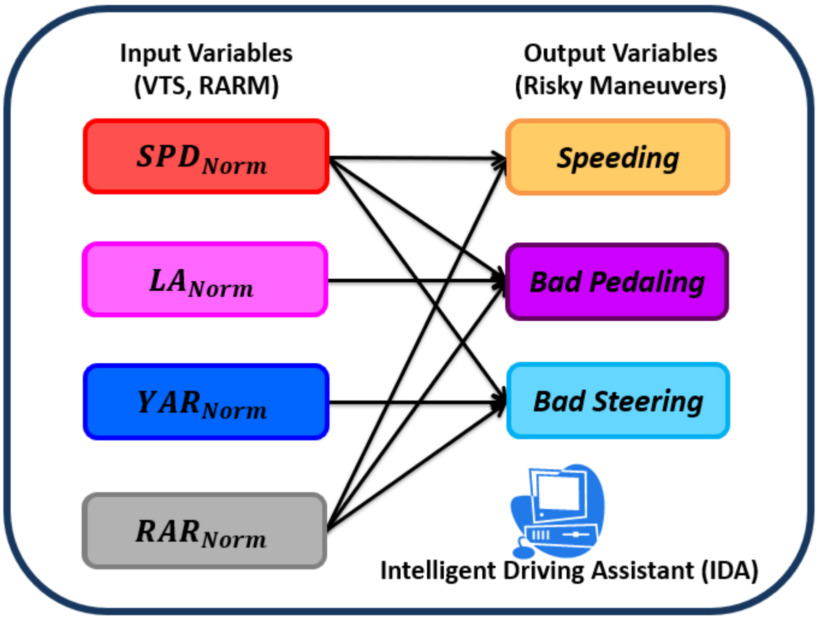


Fig. 5.5.2-1 – IDA Variables Dependency

5.5.3. System Outputs (Defuzzifying Process)

Finally, the last step consists on perform the reverse process of the beginning to the new fuzzy variables. The *defuzzifying* process allows getting a magnitude (by centroid of the area) in order to determine which driving assistance is emitted. The three (3) new fuzzy variables correspond to the established risky maneuvers: *Speeding*, *Bad Pedaling* and *Bad Steering*. It is used the same function set for each maneuver and they are defined as follows:

- *Speeding*: it is described by two (2) labels, "*Normal*" and "*High*". Fig. 5.5.3-1 shows its membership functions set.

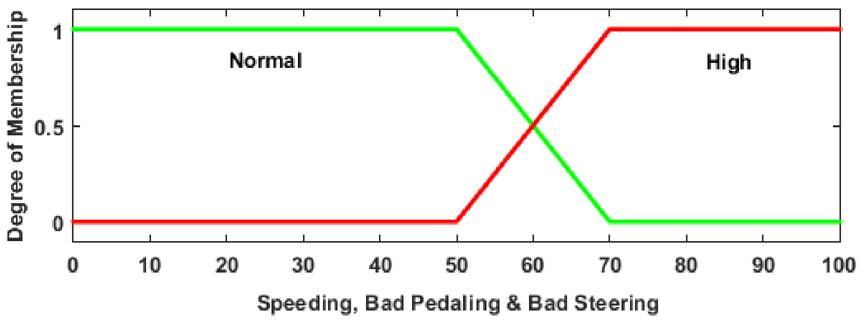


Fig. 5.5.3-1 – *Speeding* membership functions

- *Bad Pedaling*: it is described by two (2) labels, "*Normal*" and "*High*". Fig. 5.5.3-2 shows its membership functions set.

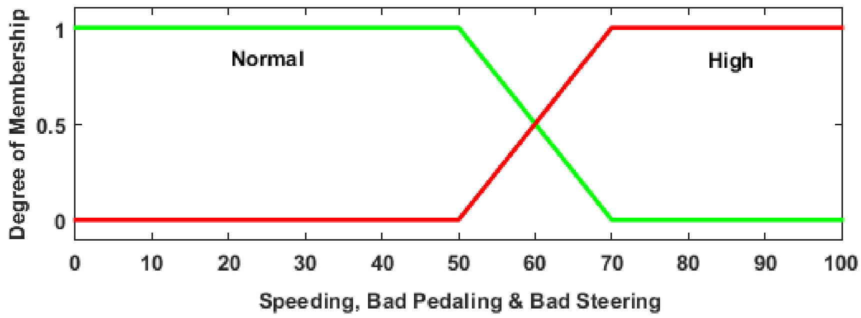


Fig. 5.5.3-2 – *Bad Pedaling* membership functions

- *Bad Steering*: it is described by two (2) labels, "*Normal*" and "*High*". Fig. 5.5.3-3 shows its membership functions set.

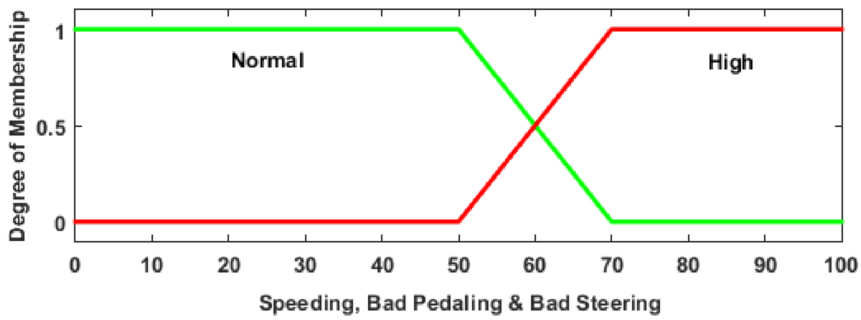


Fig. 5.5.3-3 – *Bad Steering* membership functions

As a result, from the combination of input and output membership functions along with the set of fuzzy inference rules, a driving assistance is obtained.

5.6. Driving Assistant Results (DAR) and Tips

As mentioned previously, it is expected that the assistant issues driving recommendations for the established risky maneuver (Section 4.2.4). In this sense, for each detected maneuver a driving advice has been set, making a total of three advices. The established tips are: "*Slow Down*" when detecting *Speeding*, "*Brake Slowly*" when detecting *Bad Pedaling* and "*Soften Steering*" when detecting *Bad Steering*. In the case that more than one maneuver is detected, the system issues the advices in the same order that they have been presented (*Slow Down*, *Brake Slowly* and then *Soften Steering*.) Fig. 5.6-1 shows driving assistant tips for each risky maneuver.

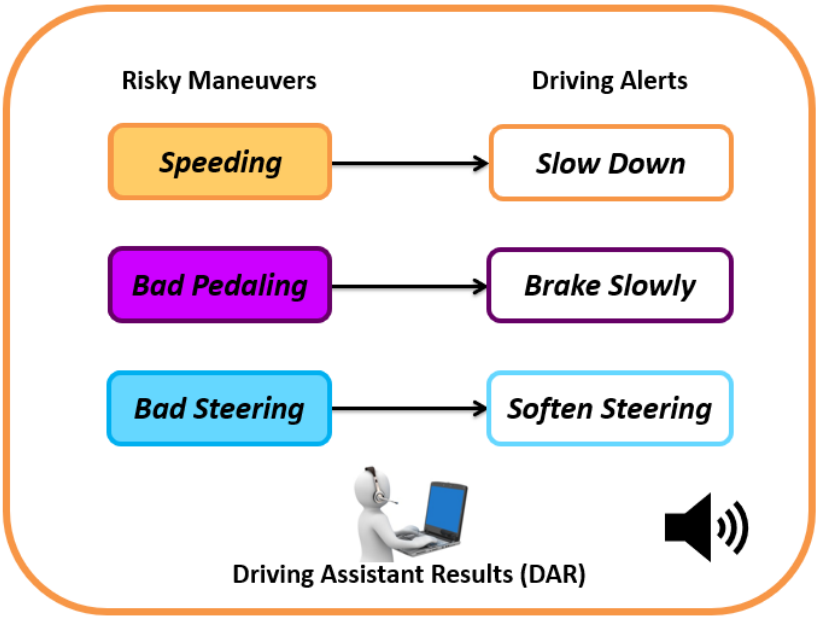


Fig. 5.6-1 – Driving Assistant Alerts: *Slow Down*, *Brake Slowly* and *Soften Steering*

5.7. Final Remarks

According to the content exposed in this chapter, the methodological framework established for the implementation of the intelligent driving assistant follows the same structural scheme presented in Chapter 4. It should be noted that, while Chapter 4 presents the conceptual idea of the proposed assistant, Chapter 5 describes the steps required for its construction in real environment.

After having exposed the final outputs of the driving assistant (the three assists) in Section 5.6, it is time to present the validation process of developed intelligent system. For this, then in Chapter 6, the tests and experiments carried out to evaluate functionality and efficiency of the proposed assistant are presented, together with obtained results.

PART III

EXPERIMENTS RESULTS AND CONCLUSIONS

Chapter 6

Analysis of the Experimental Results

This chapter presents the discussion and analysis of the empirical experiments and tests that have been carried out on real scenarios. The results depicted in this chapter demonstrate the utility, feasibility and reliability of the overall proposed approach presented in the previous chapters.

6.1. Experimental Design and Results

As described so far, the Intelligent Driving Assistant (IDA) seeks to support the driver by issuing driving suggestions (visual and audio alerts) in order to improve the driving performance. It is considered as a suitable driving performance those moments in which, during the experiments, none of the previously established risk maneuvers is detected or carried out, and therefore the system does not need to issue any assistance (Section 5.6). The results presented in this section illustrate the proper functioning of the intelligent assistant and how the abstraction of expert knowledge is correctly applied in the assessment of driving maneuvers.

As a support element, the assistance results obtained in the visual interface are complemented with video records to clarify situations where doubts or ambiguities arise during the post-driving analysis.

In order to quantitatively assess the performance of the IDA proposed in this work, three (3) types of tests are carried out, which evaluate the performance of the system from different perspectives. The first one consists of a functionality test, i.e., verify that the system fulfils the described requirements and its task. The second one verifies its performance (efficiency), i.e., that the assistant issues correct suggestions (alerts) in those situations that really claim it (detected risk maneuvers). And finally, the third one seeks to evaluate the incidence of the use of the assistant in the driving process.

Prior to presenting the experimental design of each mentioned test, the parameters and road scenarios in which they will be carried out are first described. Then, the results obtained from each test are exposed and analyzed. Additionally, a statistical validation of said results is made.

6.1.1. Road Scenarios

Among the characteristics of the proposed IDA, it is pointed out that the system can adapt to the driving environment (different road types), this by updating the assistant's evaluation parameters previously described in Section 5.4.1, and that is also equally suitable for any vehicle. In order to verify such versatility, a certain number of test scenarios is established (test routes). The factors taken into account for this selection were the types of road and the types of vehicle.

- **Types of Road**

With road types it is desired to demonstrate the environment adaptability. A total of three (3) routes were selected to carry out the tests. This selection was made based on the routes characteristics related to three (3) types of road infrastructures: straight sections, curved sections and intersections. The goal is to select routes which differ from each other as possible to try to address different types of road scenarios. The selected routes along with their characteristics are exposed below:

- *Route 1: Straight Road*

Fig. 6.1.1-1 shows the road of the first route. In turn, Table 6.1.1-1 presents its characteristics.

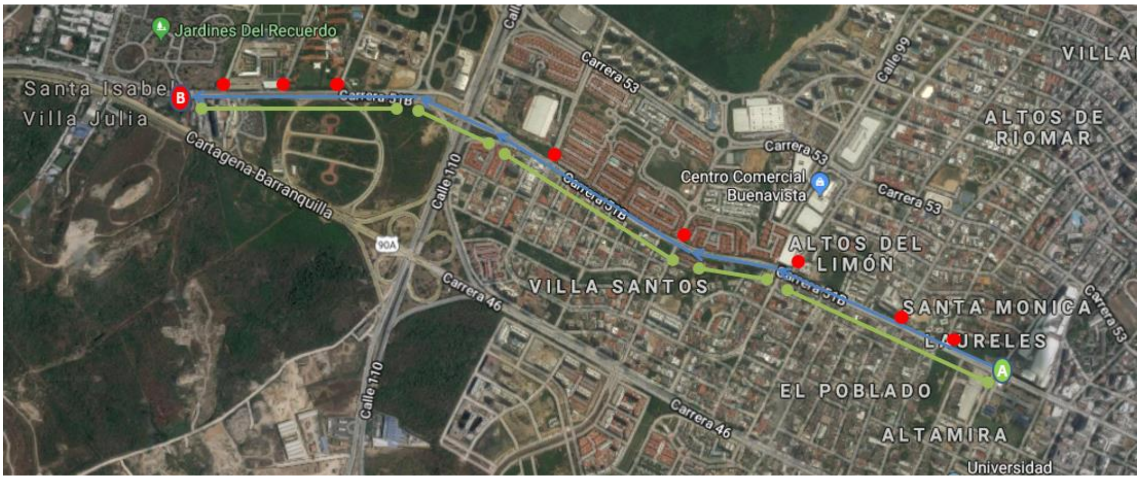


Fig. 6.1.1-1 - *Route 1 Straight Road* (A: Start Point, B: End Point)

	Route 1	
	Approx. Distance	3.5 km
	Approx. Number of Straights	5 (long straights)
	Approx. Number of Curves	0
	Approx. Number of Intersections	8

Table 6.1.1-1 – *Route 1* Details

- *Route 2: Curved Road*

Fig. 6.1.1-2 shows the road of the second route. In turn, Table 6.1.1-2 presents its characteristics.

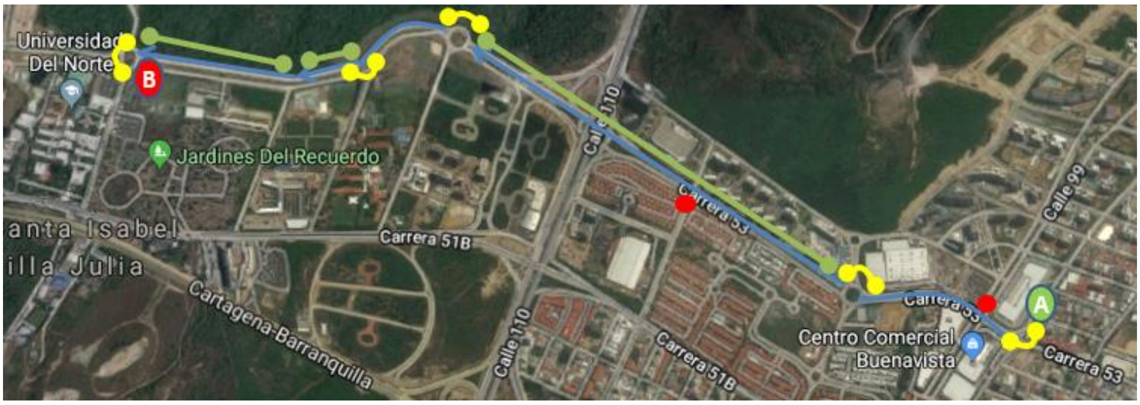


Fig. 6.1.1-2 - *Route 2 Curved Road* (A: Start Point, B: End Point)

Route 2		
	Approx. Distance	3 km
	Approx. Number of Straights	3
	Approx. Number of Curves	5
	Approx. Number of Intersections	2

Table 6.1.1-2 – *Route 2* Details

- *Route 3: Intersection Road*

Fig. 6.1.1-3 shows the road of the third route. In turn, Table 6.1.1-3 presents its characteristics.

Fig. 6.1.1-3 - *Route 3 Intersection Road* (A: Start Point, B: End Point)

Route 3		
	Approx. Distance	1.76 km
	Approx. Number of Straights	9
	Approx. Number of Curves	6
	Approx. Number of Intersections	9

Table 6.1.1-3 – *Route 3* Details

- **Types of Vehicle**

With vehicle types it is desired to demonstrate the compatibility and system management. For this, the mass of the vehicles was used as a selection criterion, considering:

- *Light Vehicles* (V_1): Those with a mass less than 1000 kg. This category includes short and small vehicles of Hatchback type.
- *Heavy Vehicles* (V_2): Those with a mass greater than 1000 kg. This category includes long and large vehicles of Sedan type.

6.1.2. Functionality Test

As previously mentioned, the purpose of the functionality test is to make sure that the developed system complies with what was promised, its assistance work when risk maneuvers are detected. For it, this is demonstrated by presenting some examples of the assistant's performance in different road scenarios.

➢ **Functionality Test Results**

As stated above, it is important to ensure the correct operation of the IDA. This is to verify that, for the established requirements and the different routes carried out, the system detects risk maneuvers and issues alerts coherently according to the behavior of the monitored variables (*SPD*, *LA*, *YAR*) and the characteristics of the environment (*RAR*) (Section 5.4.1). In order to illustrate this, below there are presented some samples of the system operation for one driver in each route.

- **Route 1: Straight Road Sample**

For an example of *Route 1*, Fig. 6.1.2-1 shows a segment of the route where there can be seen some of the resulting driving alerts. Here it is possible to observe both, the location of the alerts and the behavior of the variables over time during this segment. Likewise, Fig. 6.1.2-2 presents the assessment parameters characteristics of this route.

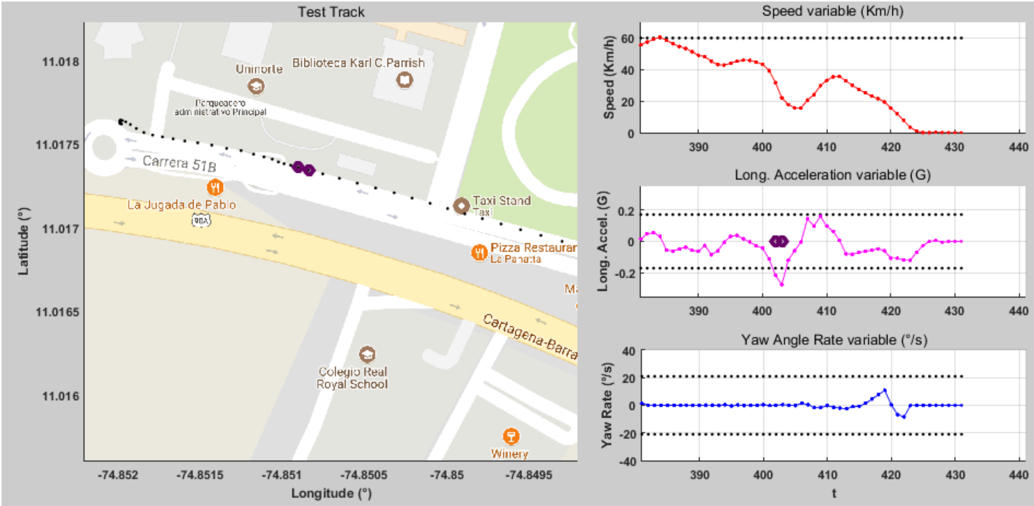


Fig. 6.1.2-1 – Segment of *Route 1* for Driver D_1 Assistance Results

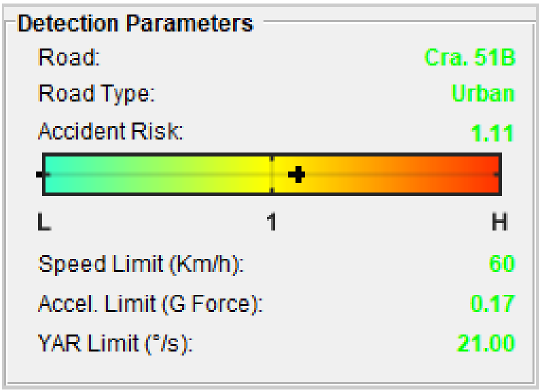


Fig. 6.1.2-2 – *Route 1* Assessment Parameters

As the whole route is on the same road section, the assessment parameters remain constant throughout the journey. In this case, there are found the parameters corresponding to the "Cra. 51B", which consist of an *Urban* road (Section 5.4.1).

From all the alerts obtained in this route, the segment of Fig. 6.1.2-1 only presents two of *Bad Pedaling*. In those instants of time it is achieved an acceleration of -0.27 G (braking), which is equivalent to a "*Strong*" *LA* according to the assessment parameters and the membership functions established for this variable (Sections 5.4.1 and 5.5.1). At the same time, such *LA* is developed at a speed of 22.04 km/h, what is equivalent to a "*Low*" *SPD* (for the same reasons), and in turn the "Cra. 51B" has an accident risk of 1.11, what amounts to a "*Normal*" *RAR*. So that, for these conditions, the fuzzy rule number 7 is activated (Table 5.5.2-1), a risk maneuver is detected and therefore the *Brake Slowly* alert is issued. In this case, the reasoning that follows the assistant is that for a road with normal accident rate, regardless of whether the vehicle is going at low speed, if an abrupt acceleration is made, the system equally considers it as a risky maneuver.

Fig 6.1.2-3 shows the number of risk maneuvers / driving alerts gotten during the trip. Here there were obtained zero (0) *Slow Down* alerts, four (4) *Brake Slowly* and one (1) *Soften Steering*, having a total of five (5) alerts.

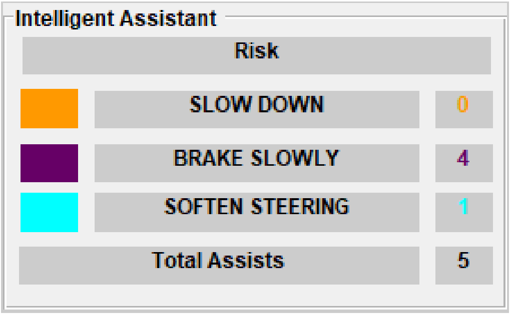


Fig. 6.1.2-3 – *Route 1*: Driver D_1 Assistance Results

- **Route 2: Curved Road Sample**

On the other hand, Fig. 6.1.2-4 shows a segment of the *Route 2*. In the same way as *Route 1*, as the route is always on the same road section, the assessment parameters remain constant during the trip, only that now it is the "Cra. 53". Although it is an *Urban* road too, there is a different *RAR* from that of "Cra. 51B". Fig. 6.1.2-5 presents the assessment parameters of this route.

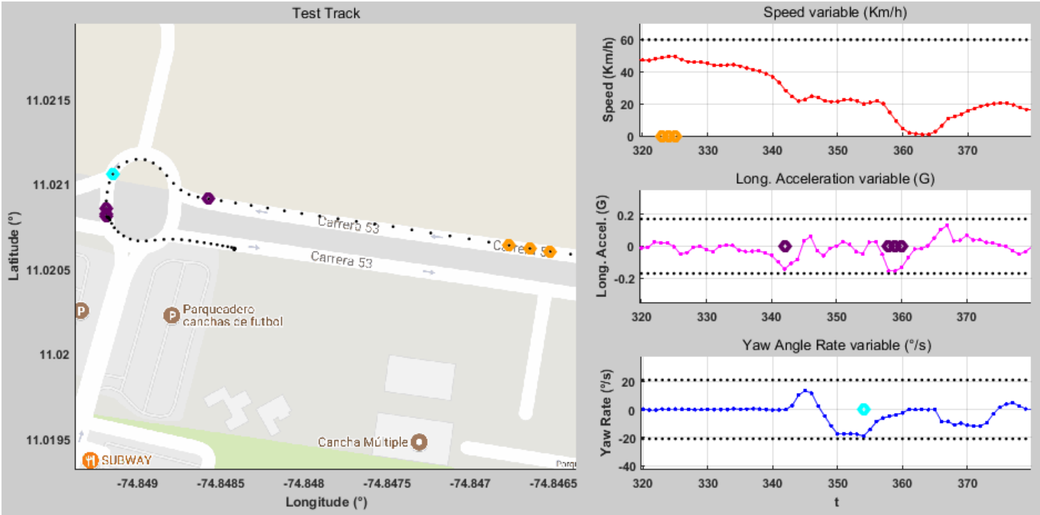


Fig. 6.1.2-4 – Segment of *Route 2* for Driver D_1 Assistance Results

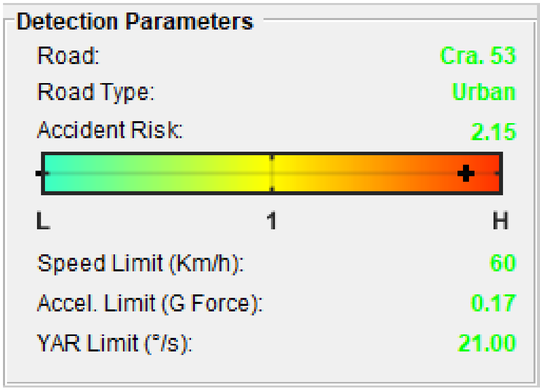


Fig. 6.1.2-5 – *Route 2* Assessment Parameters

In the road segment shown in Fig. 6.1.2-4, again from all alerts obtained, there are only observed three *Speeding* alerts, four *Bad Pedaling* and one *Bad Steering*. In each of these cases, there is the premise that the vehicle is on a road with a "*High*" *RAR* (an accident risk of 2.15). So, for the *Speeding* alerts, it is reached a speed of 49.47 km/h (which corresponds to a "Low - Normal" *SPD* level), activating then the fuzzy rule number 3 (Table 5.5.2-1). For *Bad Pedaling* alerts, accelerations up to -0.15 G (braking) are reached ("*Normal*" level of *LA*) at speeds of 28 km/h approximately ("*Low*" *SPD*), thus activating rule 10. And then, for the *Bad Steering* alert, having a turning angle of -19 °/s (left turn, which is interpreted as a "*Normal - High*" *YAR*) with a speed of 20 km/h ("*Low*" *SPD*), the rule number 15 comes to play.

Fig. 6.1.2-6 shows the risk maneuvers / alerts gotten in *Route 2*. In this case, there were obtained thirty-seven (37) *Slow Down* alerts, eleven (11) *Brake Slowly* and one (1) *Soften Steering*, having a total of forty-nine (49) alerts.

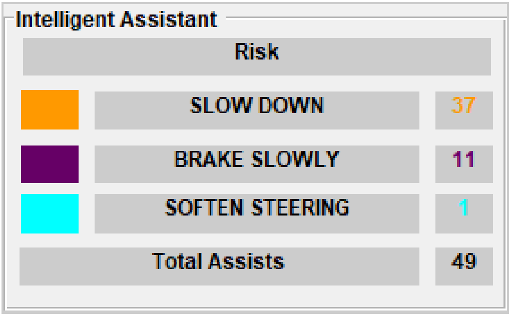


Fig. 6.1.2-6 – *Route 2*: Driver D_1 Assistance Results

- **Route 3: Intersection Road Sample**

Finally, unlike the previous routes, *Route 3* passes through different road sections, so that the assessment parameters do not remain constant, but they adapt according to the road section in which the vehicle is located. In this respect, all the road sections of *Route 3* correspond to *Local* roads, however, each one has its own *RAR*, making that some road sections have a higher accident risk than others. Fig. 6.1.2-7 shows a segment of the route where there can be observed some resulting driving alerts, and then Fig. 6.1.2-8 presents the assessment parameters of roads "Cra. 75a" and "Cl. 92" respectively.

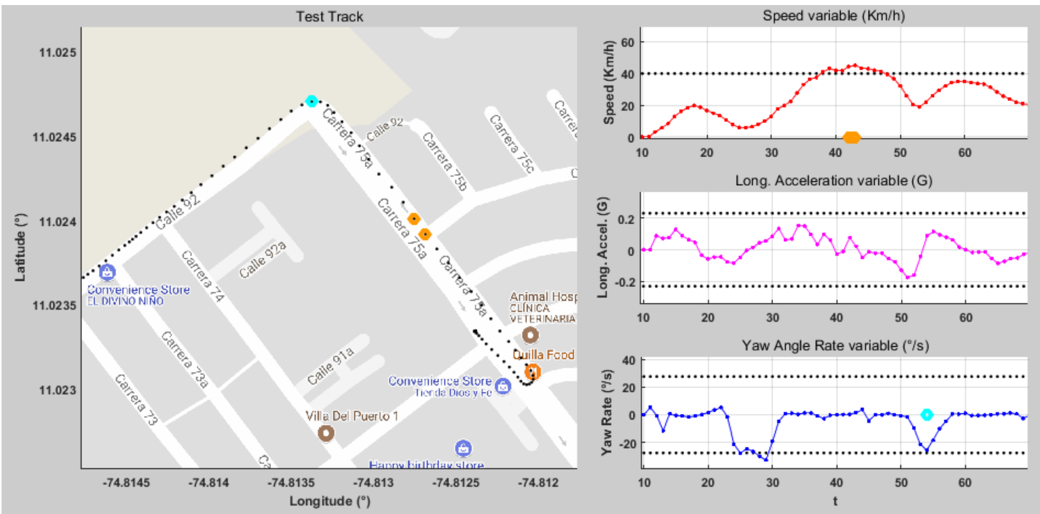


Fig. 6.1.2-7 – Segment of *Route 3* for Driver D_1 Assistance Results

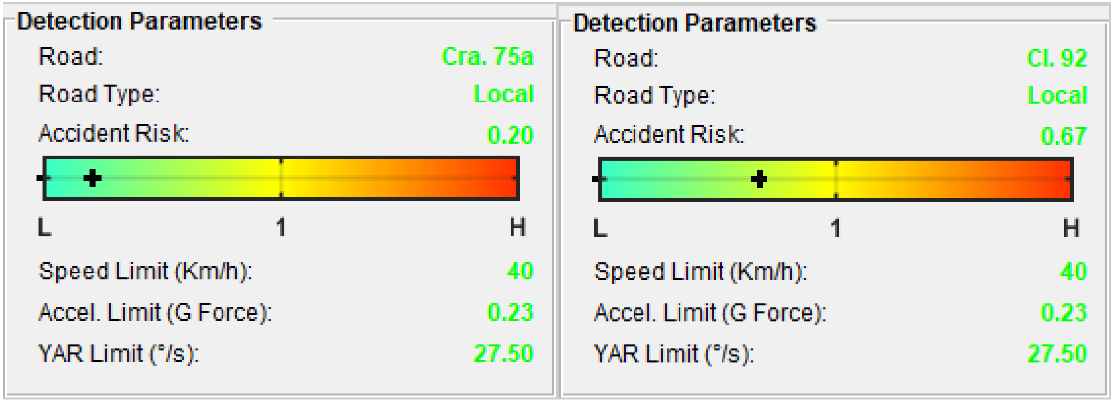


Fig. 6.1.2-8 – *Route 3* Assessment Parameters for “Cra. 75a” and “Cl. 92”

Fig. 6.1.2-7 shows three driving alerts, the first two of *Speeding* and the third one of *Bad Steering*. In the first case, the vehicle is on a road with “*Low*” accident risk (*RAR* of 0.2), and in those instants it manages to reach a speed of 45.15 km/h, what amounts to a “*Normal - High*” level of *SPD* for that route, thus activating rule number 1 (Table 5.5.2-1). Here the assistant, regardless of the low degree of road accident, also considers this excess as a risky maneuver. And in the second case, for the *Bad Steering* alert, the vehicle passes to a new road section now having a new *RAR* (0.67), which corresponds to a “*Low - Normal*” level of accident. When making a turn of -25.4°/s (left turn, “*Normal - High*” *YAR*) at a speed of 22 km/h (“*Low*” *SPD*), rule number 13 comes into action.

Fig. 6.1.2-9 shows the resulting risk maneuvers / driving alerts on *Route 3*. In this case, there were obtained nine (9) *Slow Down* alerts, zero (0) *Brake Slowly* and one (1) *Soften Steering*, having a total of ten (10) alerts.

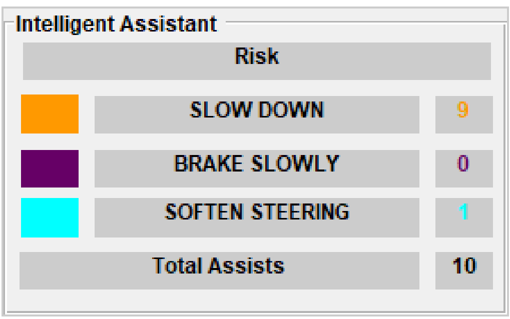


Fig. 6.1.2-9 – *Route 3*: Driver D_1 Assistance Results

6.1.3. Efficiency Test

The efficiency test is carried out in order to determine the degree of effectiveness of the overall driving assistant. To perform this test, it is necessary to know what outputs (suggestions/alerts) are given by the assistant during each journey. The objective is to contrast the number of correct alerts against the number of total alerts issued. In the current case, there are considered correct assistances those that for the behavior of monitored variables (values), the fuzzy inference rules are effectively fulfilled.

- **Procedure**

The methodology for performing this test consist of taking a set of driving samples (from different people, for each route and vehicle), and apply to each of these the analysis made by the IDA. As it is desired to contrast correct against total alerts issued, the average correct alerts provided by the driving assistant is adopted as the assessment metric.

The distinction between correct and incorrect alerts is made through an inspection process in which the behavior of the telemetry data is considered (monitored signals). These signals showed certain erratic behaviors in areas where the satellite signal was temporarily interrupted during the tests. This implies inaccurate data delivered by the VTS, and therefore a misunderstanding of the risk maneuvers performed by the assistant when they do not really happen. Fig. 6.1.3-1 illustrates such erratic behavior in the telemetry signals.

Taking into account the established factors (Section 6.1.1) and the chosen metric, the variables involved in the development of the experiment are worked as shown below.

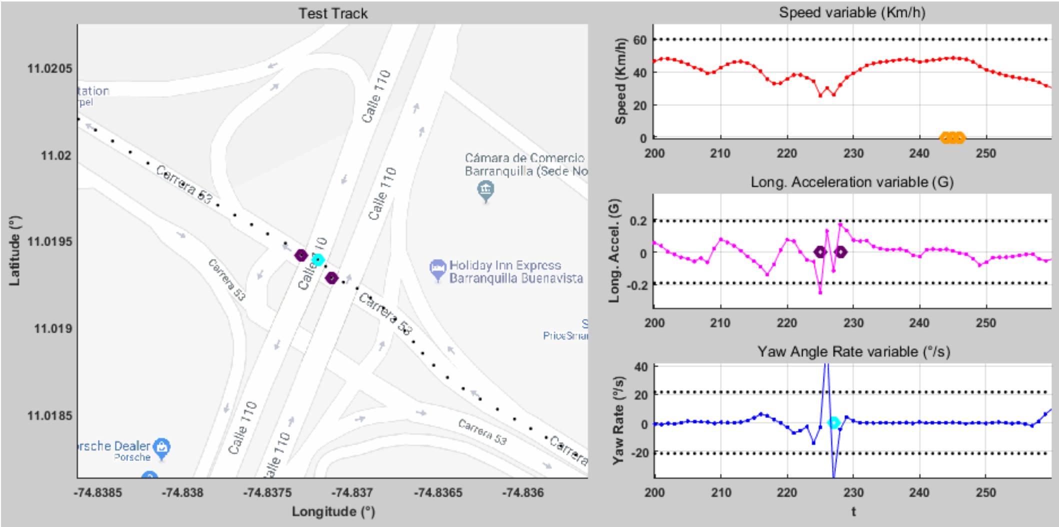


Fig. 6.1.3-1 – Telemetry data erratic behavior: *Long. Acceleration* (purple) and *Yaw Angle Rate* (blue)

- **Interest Response (Dependent Variable)**
  - Average Percentage of Correct Alerts [%]
- **Treatment Factors (Independent Variable)**
  - Route
  - Type of Vehicle
- **Levels by Factor**
  - Route: Three (3) levels, *Route 1*, *Route 2* and *Route 3*.
  - Type of Vehicle: Two (2) levels, *Light Vehicle* (V_1) and *Heavy Vehicle* (V_2).
- **Total Number of Experiments (TNE)**

As it is desired to study simultaneously the effects of the factors, a "Factorial Experiment" is developed, so that observations of all possible combinations of the levels of each factor can be obtained (Wapole, Myers, Myers & Ye, 2012). So, to determine the *TNE* it is used Eq. 12:

$$TNE = r \prod_{i=1}^{k} n_i \qquad (12)$$

Where:

- r: Number of repetitions to be made.
- k: Number of factors to consider.
- n_i: Number of levels per factor.

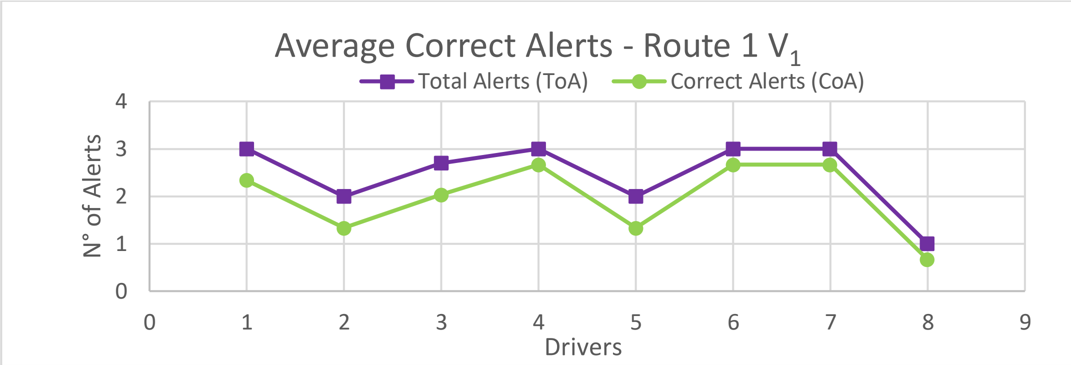
According to what is established for this test, there are two factors ($k = 2$), one with three levels ($n_1 = 3$) and the other with two ($n_2 = 2$). For the r value, it is necessary to select a proper number of repetitions, so that the experiment is consistent, and a statistical analysis can be performed. According to literature, works related to the development of IDAs indicate that, due to the large number of factors that influence the behavior of this type of systems (most of which are uncontrollable), it is possible to affirm that the behavior of the mean value (average of correct alerts in this case) follows that of a variable with *Normal* distribution (Quintero & Cuervo, 2017). In such cases, $r = 30$ is considered an adequate value for the experiments, a smaller value would lead to approximate the behavior of the mean to a variable with *t-student* distribution, whereas a higher value would imply continuing to work it as a *Normal* distribution (Wapole et. al, 2012). For feasible reasons, it was decided to set an amount of eight (8) drivers to perform three (3) repetitions of each case for this test ($r = 24$), obtaining a total of 144 experiments ($TNE = 144$).

- **Efficiency Test Results**

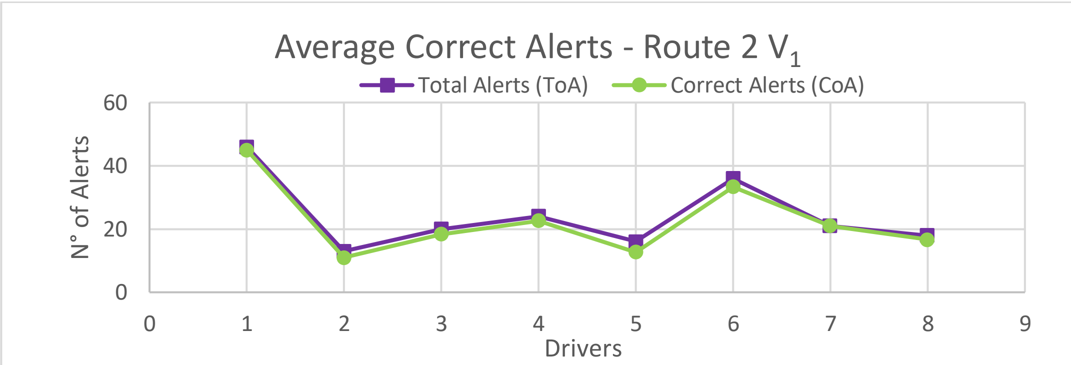
Following the design described above, below there are presented the results obtained in the efficiency test. These are organized according to the type of vehicle and the route made. Again, the objective is to contrast the number of correct alerts against the total alerts issued.

- **Total Correct Alerts on all routes for V_1 (Light Vehicle)**

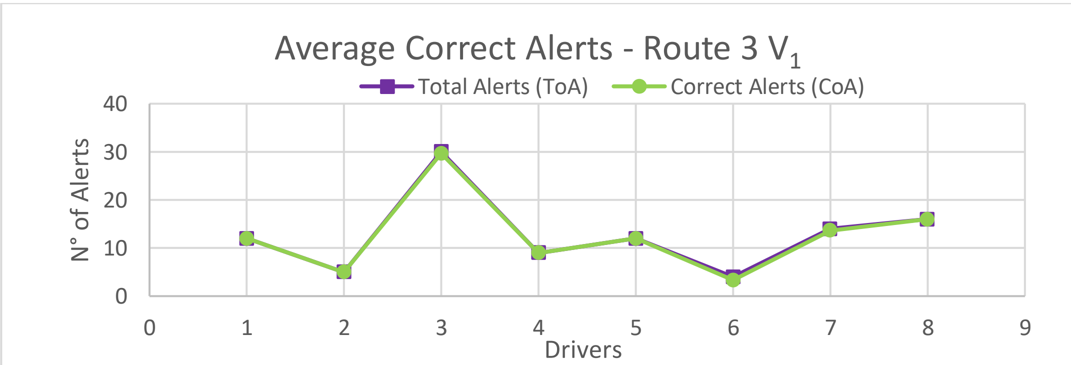
First, Fig. 6.1.3-2 shows the average correct alerts obtained by each driver in each route for the *light vehicle* (V_1), and then, Fig. 6.1.3-3 shows the average correct alerts obtained by each driver but in all routes. For this instance, Table 6.1.3-1 presents the percentage of correct alerts obtained by each driver exposed in Fig. 6.1.3-2 and 6.1.3-3.



(a)



(b)



(c)

Fig. 6.1.3-2 – Average Total Correct Alerts on each route for V_1 (*Light Vehicle*): (a) *Route 1*, (b) *Route 2* and (c) *Route 3*, Total Alerts (purple) and Correct Alerts (green)

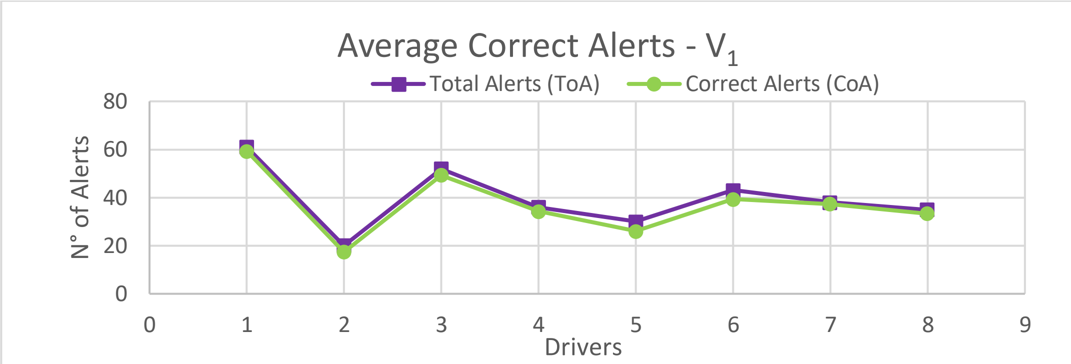


Fig. 6.1.3-3 – Average Total Correct Alerts on all routes for V_1 (*Light Vehicle*), Total Alerts (purple) and Correct Alerts (green)

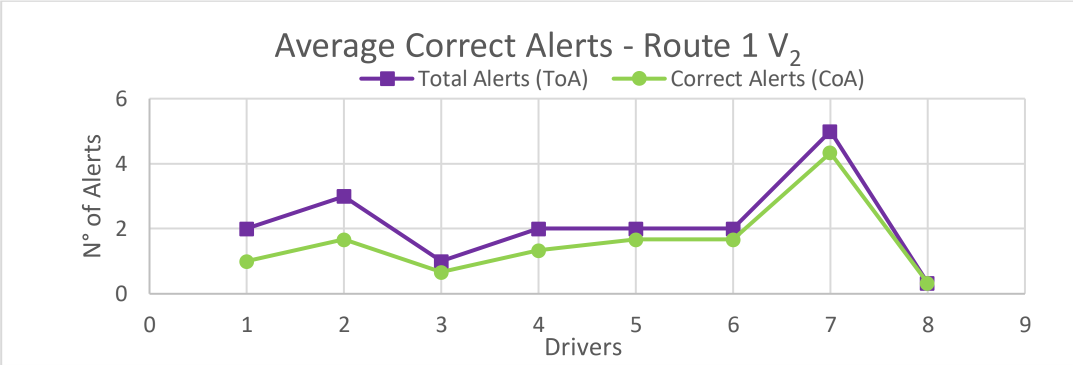
Percentage of Correct Alerts [%]									
Routes \ Drivers	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	Avg.
Route 1	77.8	66.7	75.3	88.9	66.7	88.9	88.9	66.7	77.5
Route 2	97.8	84.6	91.7	94.4	79.2	92.6	100	92.6	91.6
Route 3	100	100	98.9	100	100	83.3	97.6	100	97.5
All Routes	97.3	86.7	94.9	95.4	86.7	91.5	98.2	95.2	93.2

Table 6.1.3-1 – Percentage of Correct Alerts for V_1 (*Light Vehicle*)

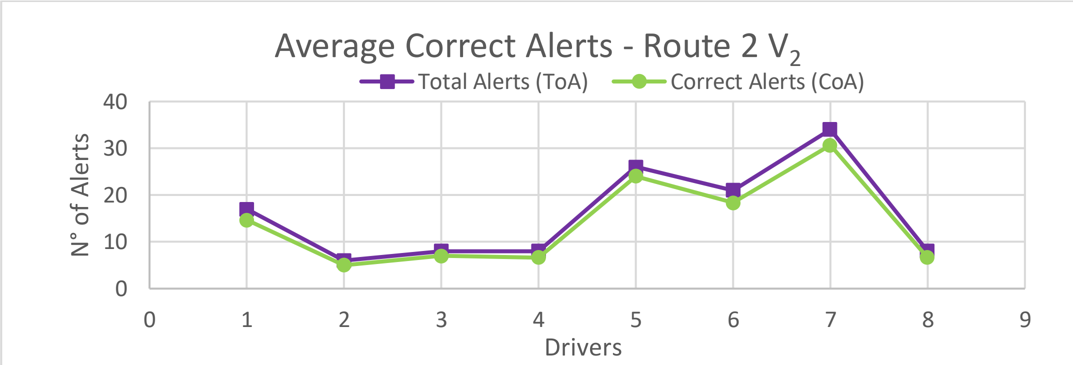
In the case of *Route 1*, it possible to observe that there was obtained a high percentage of correct alerts for all drivers, resulting a total average of 77.5%, in the same way, in *Route 2* there was a higher average of correct alerts for all drivers as well, obtaining a total average of 91.6%, and for *Route 3*, as in *Route 2*, it can be seen again a high average for all drivers, obtaining in this case a total of 97.5%. Consequently, in the global case of V_1, considering the total alerts obtained for all routes, effectively there is a high number of correct alerts issued, getting a total average of 93.2%.

- **Total Correct Alerts on all routes for V_2 (Heavy Vehicle)**

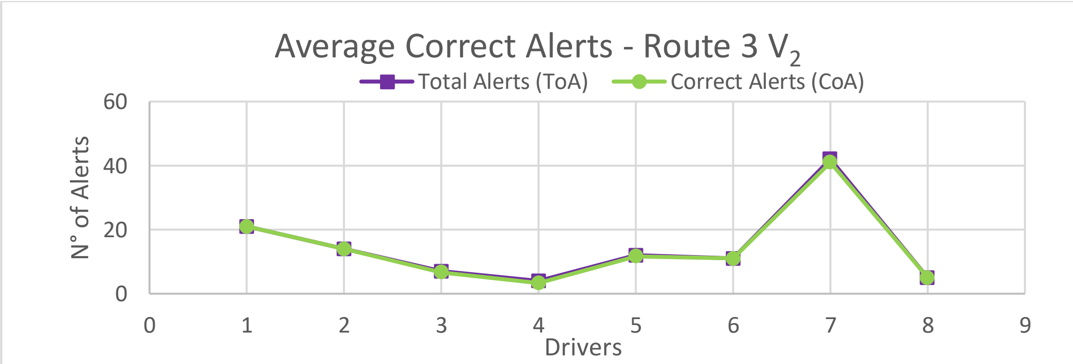
Following the same structure, know there are exposed the efficiency results obtained for the *heavy vehicle* (V_2). In the same way, Fig. 6.1.3-4 shows the average correct alerts obtained by each driver, in each route; and then, Fig. 6.1.3-5 shows the average correct alerts obtained by each driver but in all routes. In this respect, Table 6.1.3-2 indicates the percentage of correct alerts obtained by each driver in Fig. 6.1.3-4 and 6.1.3-5.



(a)



(b)



(c)

Fig. 6.1.3-4 – Average Total Correct Alerts on each route for V_2 (*Heavy Vehicle*): (a) *Route 1*, (b) *Route 2* and (c) *Route 3*, Total Alerts (purple) and Correct Alerts (green)

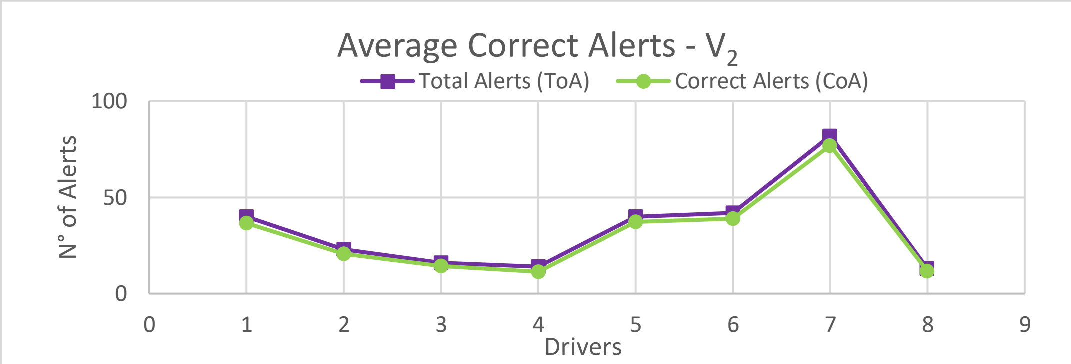


Fig. 6.1.3-5 – Average Total Correct Alerts on all routes for V_2 (*Heavy Vehicle*), Total Alerts (purple) and Correct Alerts (green)

Percentage of Correct Alerts [%]									
Drivers / Routes	**D_1**	**D_2**	**D_3**	**D_4**	**D_5**	**D_6**	**D_7**	**D_8**	**Avg.**
Route 1	50.0	55.6	66.7	66.7	83.3	83.3	86.7	100	74.0
Route 2	86.3	83.3	87.5	83.3	92.3	87.3	90.2	83.3	86.7
Route 3	100	100	95.2	83.3	97.2	100	97.6	100	96.7
All Routes	91.7	89.9	89.6	81.0	93.3	92.9	93.9	89.7	90.2

Table 6.1.3-2 – Percentage of Correct Alerts for V_2 (*Heavy Vehicle*)

In *Route 1*, again it can be seen that there was a high percentage of correct alerts, resulting a total average of 74%, similarly as in V_1, in *Route 2* there was a higher average of correct alerts for all drivers, obtaining know a total average of 86.7%, and for *Route 3*, there was also a high average of correct alerts, obtaining in this case a total of 96.7%. Therefore, in the global case of V_2, considering the total alerts obtained for all routes, indeed there is a high number of correct alerts issued, resulting in a total average of 90.2%.

- **Total Correct Alerts on all routes for all vehicles (V_1 and V_2)**

As a closing point, Fig. 6.1.3-6 shows the average correct alerts obtained by each driver comprising all routes and all vehicles. Table 6.1.3-3 presents the percentage of correct alerts in this figure.

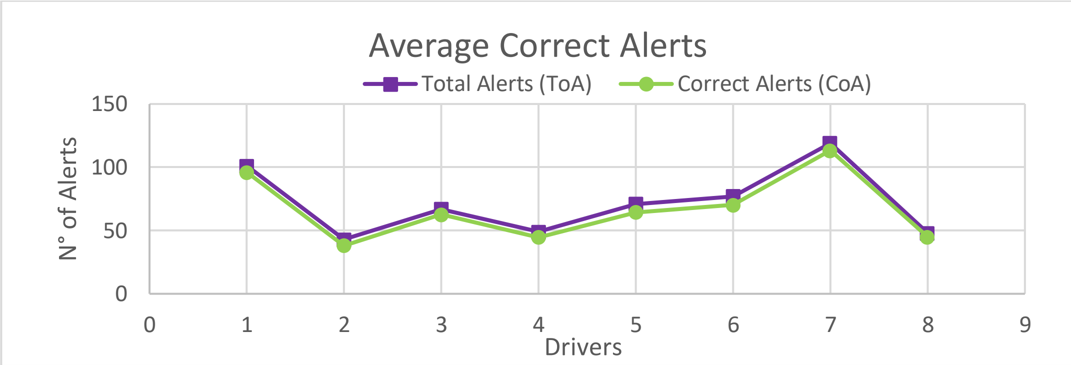


Fig 6.1.3-6 – Average Total Correct Alerts on all routes for all vehicles, Total Alerts (purple) and Correct Alerts (green)

Percentage of Correct Alerts [%]										
Drivers / Routes	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	Avg.	Std. Dev.
All Routes V_1 & V_2	95.0	88.4	93.5	91.2	90.6	91.3	95.2	93.8	92.4	2.4

Table 6.1.3-3 – Percentage of Correct Alerts on all routes for all vehicles

In this instance, it is obtained a global result of the correct alerts percentage of each driver on all routes (*Route 1*, *Route 2* and *Route 3*) for all vehicles (V_1 and V_2), getting a global average of 92.4% with a standard deviation of 2.4%.

6.1.4. Driving Performance Test

The purpose of this test is to evaluate the incidence of the use of the assistant in the driving process. To do this, it is desired to study the performance of drivers in terms of the number of risk maneuvers made.

- **Procedure**

The methodology to carry out this test consist of taking samples of routes made by drivers (on each route) for two cases, when using and not using the assistant. The selected evaluation metric is the average decrease in the number of risk maneuvers performed. First, the routes are performed with the system in operation, but disabling the hearing alerts, so that the journey is made, and the detected risk maneuvers are still recorded. Later, the same route is repeated with the system in operation, but this time enabling the hearing alerts. It should be noted that, although the assistant is responsible for issuing driving tips, it remains on the driver to follow or not the assistances. Again, taking into account the established factors (Section 6.1.1) and the chosen metric, the variables involved in the development of the experiment are worked as shown below.

- **Interest Response (Dependent Variable)**
  - Average Decrease Percentage of Risk Maneuvers [%]
- **Treatment Factors (Independent Variables)**
  - Route
  - Type of Vehicle
  - Use of the IDA
- **Levels by Factor**
  - Route: Three (3) levels, *Route 1*, *Route 2* and *Route 3*.
  - Type of Vehicle: Two (2) levels, *Light Vehicle* (V_1) and *Heavy Vehicle* (V_2).
  - Use of the IDA: Two (2) levels, *Driver with IDA* (*Assisted*) and *Driver without IDA* (*Not Assisted*).
- **Total Number of Experiments (TNE)**

In the same way, as it is desired to observe the simultaneous effect of the established factors, a "Factorial Experiment" is developed which is governed by the same Eq. 12.

$$TNE = r \prod_{i=1}^{k} n_i \tag{12}$$

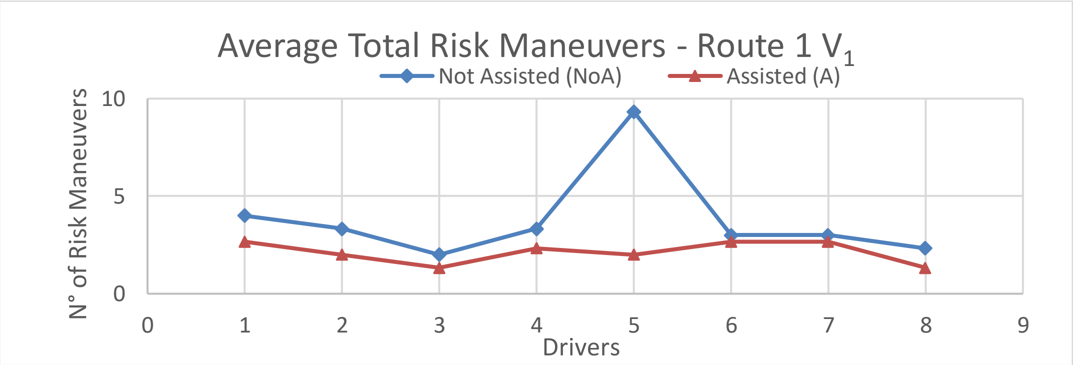
Only that, for this case, there are three factors ($k = 3$), the first and the second ones with the same previous levels ($n_1 = 3, n_2 = 2$) and the third one with two levels ($n_3 = 2$). For the same reasons stated in the previous section (Section 6.1.3), there are selected eight (8) drivers to perform three (3) repetitions of each case for this test ($r = 24$), obtaining a total of 288 experiments ($TNE = 288$).

➢ Driving Performance Test Results

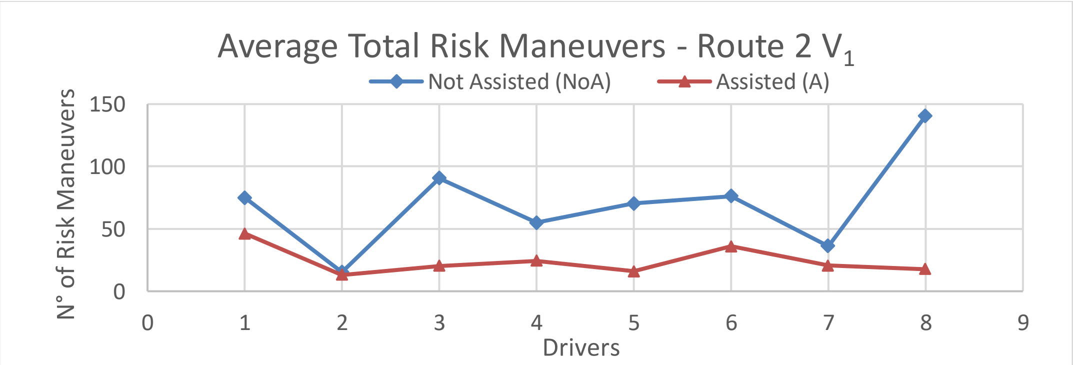
Based on the design described above, below there are presented the results obtained in the driving performance test. Following the same order of the efficiency test results, these are organized according to the type of vehicle and the route made. In this case, the objective is to contrast the amount of risk maneuvers / alerts obtained when using and not using the assistance.

- **Total Risk Maneuvers on all routes for V_1 (Light Vehicle)**

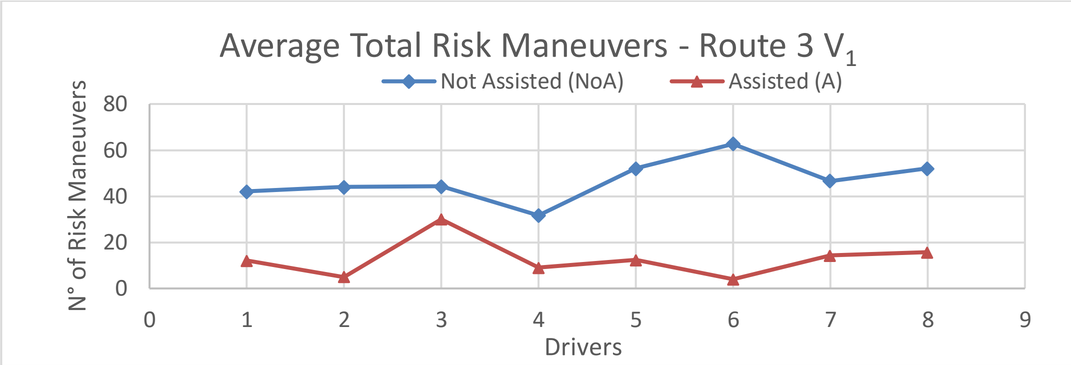
First, Fig. 6.1.4-1 shows the average total risk maneuvers obtained by each driver in each route for the *light vehicle* (V_1), in both driving scenarios (*assisted* and *not assisted* trip); and then, Fig. 6.1.4-2 shows the average total risk maneuvers obtained by each driver but in all routes. In this respect, Table 6.1.4-1 indicates the decrease percentage of the maneuvers obtained by each driver for each case exposed in Fig. 6.1.4-1 and 6.1.4-2.



(a)



(b)



(c)

Fig. 6.1.4-1 – Average Total Risk Maneuvers on each route for V_1 (*Light Vehicle*): (a) *Route 1*, (b) *Route 2* and (c) *Route 3*, Not Assisted (blue) and Assisted (red) trips

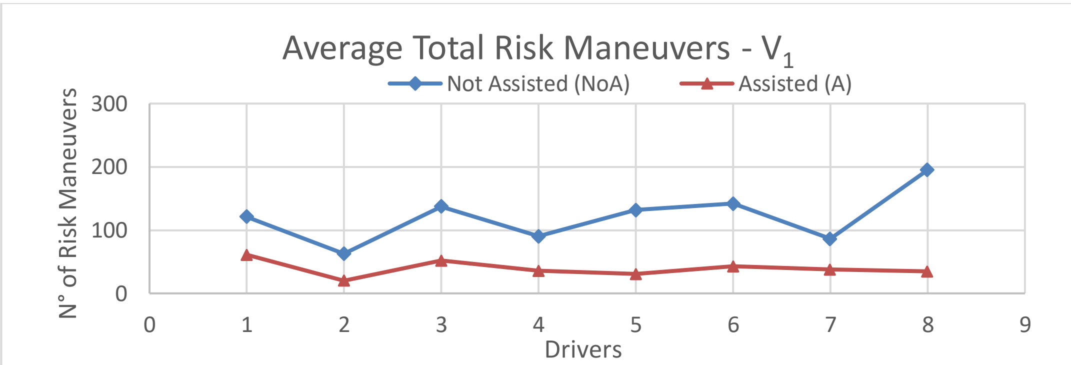


Fig. 6.1.4-2 – Average Total Risk Maneuvers on all routes for V_1 (*Light Vehicle*), Not Assisted (blue) and Assisted (red) trips

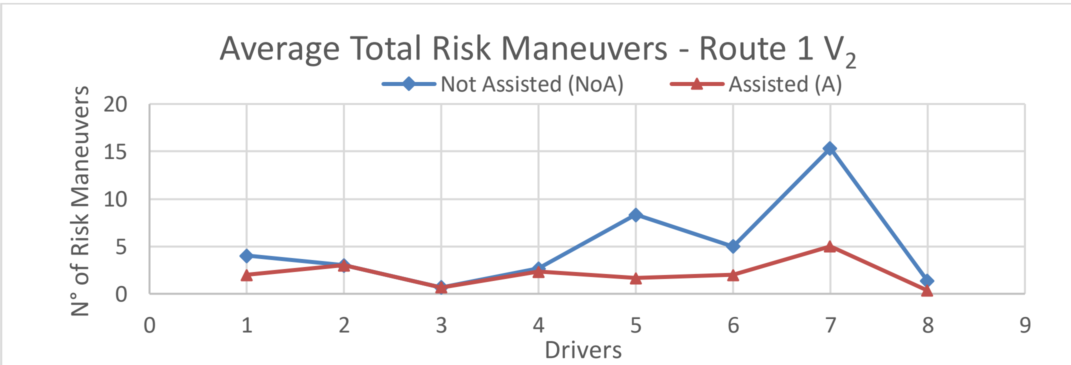
Decrease Percentage of Risk Maneuvers [%]									
Routes \ Drivers	**D_1**	**D_2**	**D_3**	**D_4**	**D_5**	**D_6**	**D_7**	**D_8**	**Avg.**
Route 1	33.3	40.0	33.3	30.0	78.6	11.1	11.1	42.9	35.0
Route 2	38.2	15.2	77.6	55.8	77.3	52.8	43.1	87.4	55.9
Route 3	71.4	88.6	32.3	71.6	76.3	93.6	69.3	69.9	71.6
All Routes	49.6	68.1	62.3	60.4	77.0	70.0	56.2	82.2	65.7

Table 6.1.4-1 – Decrease Percentage of Risk Maneuvers for V_1 (*Light Vehicle*)

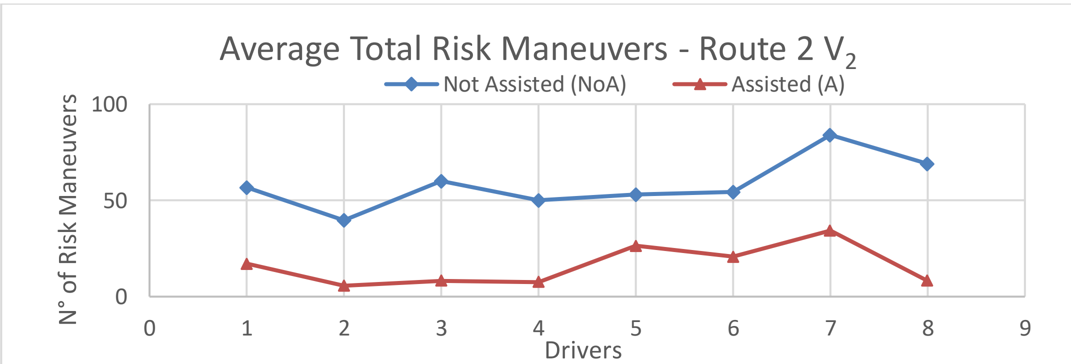
In the case of *Route 1*, it can be seen that indeed, there was a decrease in the number of risk maneuvers performed by the drivers, resulting an average decrease of 35%, likewise, in *Route 2* there was a decrease in the number of risk maneuvers for all drivers, obtaining an average decrease of 55.9%, and for *Route 3*, as in *Route 2* and *Route 1*, there was a decrease in the number of maneuvers for all drivers as well, obtaining in this case an average decrease of 71.6%. Finally and consequently, in the global case of V_1, considering the total alerts obtained for all routes, effectively there is a decrease in the number of risk maneuvers carried out by the drivers, getting a total average decrease of 65.7%.

- **Total Risk Maneuvers on all routes for V_2 (Heavy Vehicle)**

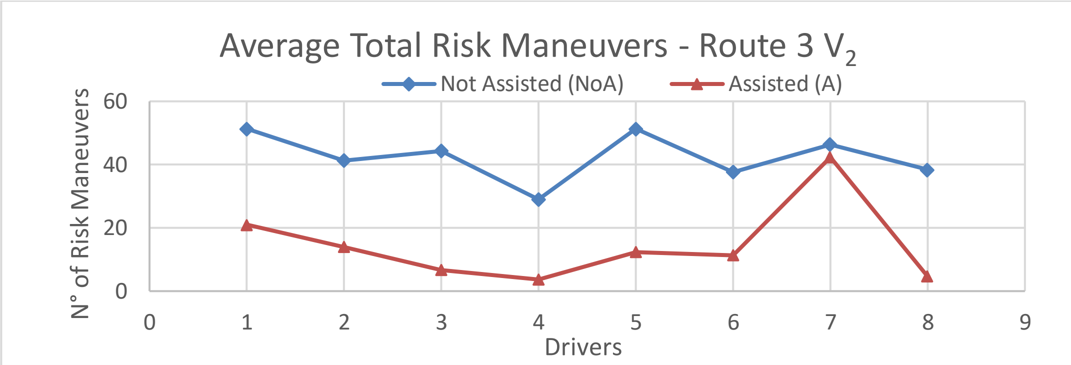
In the same way, know there are exposed the driving performance results obtained for the *heavy vehicle* (V_2). Here, Fig. 6.1.4-3 shows the average total risk maneuvers obtained by each driver, in each route, in both driving scenarios (*assisted* and *not assisted* trip); and then, Fig. 6.1.4-4 shows the average total risk maneuvers obtained by each driver but in all routes. In this instance, Table 6.1.4-2 denotes the decrease percentage of the maneuvers obtained by each driver for each case exposed in Fig. 6.1.4-3 and 6.1.4-4.



(a)



(b)



(c)

Fig. 6.1.4-3 – Average Total Risk Maneuvers on each route for V_2 (*Heavy Vehicle*): (a) *Route 1*, (b) *Route 2* and (c) *Route 3*, Not Assisted (blue) and Assisted (red) trips

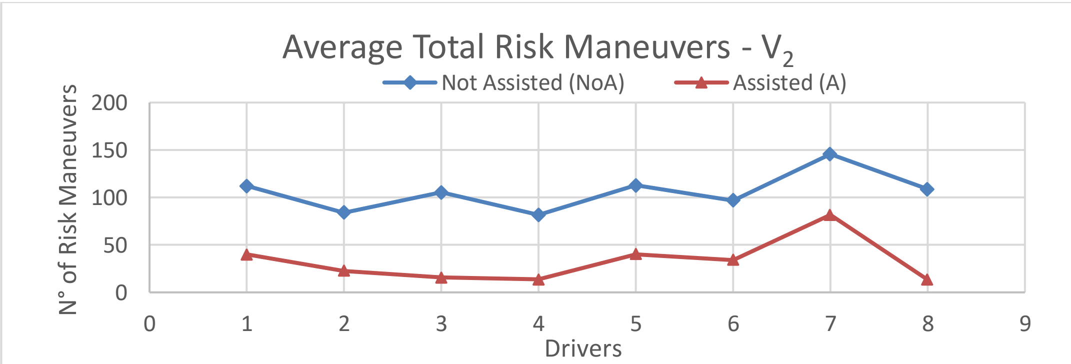


Fig. 6.1.4-4 – Average Total Risk Maneuvers on all routes for V_2 (*Heavy Vehicle*), Not Assisted (blue) and Assisted (red) trips

Decrease Percentage of Risk Maneuvers [%]									
Drivers / Routes	**D_1**	**D_2**	**D_3**	**D_4**	**D_5**	**D_6**	**D_7**	**D_8**	**Avg.**
Route 1	50.0	0.0	0.0	12.5	80.0	60.0	67.4	75.0	43.1
Route 2	70.0	85.7	86.1	84.7	50.3	62.0	59.1	87.9	73.2
Route 3	59.1	66.1	85.0	87.4	76.0	69.9	8.6	87.8	67.5
All Routes	64.3	73.0	85.1	83.3	64.2	64.9	43.9	87.7	70.8

Table 6.1.4-2 – Decrease Percentage of Risk Maneuvers for V_2 (*Heavy Vehicle*)

In *Route 1*, again it can be seen that there was a decrease in the number of risk maneuvers performed by the drivers, except for drivers D_2 and D_3 in this case, resulting an average decrease of 43.1%, however, in *Route 2* there was a decrease in the number of maneuvers for all drivers, obtaining know an average decrease of 73.2%, and for *Route 3*, there was also a decrease in the number of maneuvers for all drivers, obtaining an average decrease of 67.5%. Therefore, in the global case of V_2, considering the total maneuvers obtained for all routes, in effect there is a decrease in the number of risk maneuvers carried out by the drivers like in V_1, getting a total average decrease of 70.8%.

- **Total Risk Maneuvers on all routes for all vehicles (V_1 and V_2)**

As a closing point, Fig. 6.1.4-5 shows the average total risk maneuvers obtained by each driver covering all routes and all vehicles, and Table 6.1.4-3 presents the decrease percentage of the maneuvers in this figure.

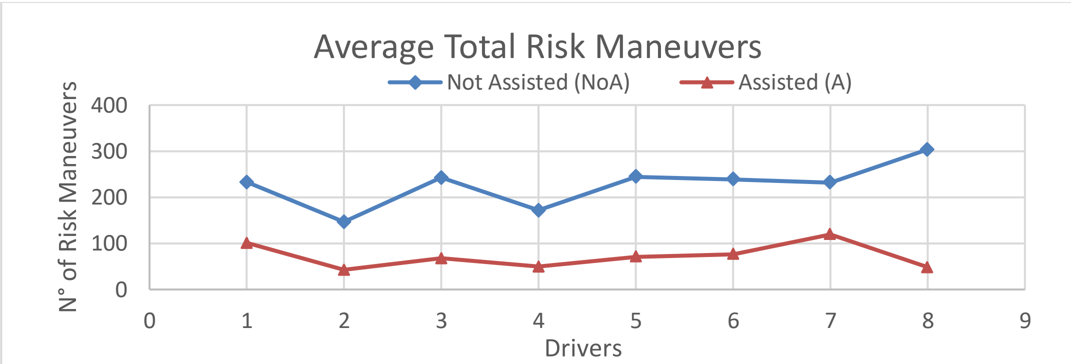


Fig 6.1.4-5 – Average Total Risk Maneuvers on all routes for all vehicles, Not Assisted (blue) and Assisted (Red) trips

Decrease Percentage of Risk Maneuvers [%]										
Drivers / Routes	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	Avg.	Std. Dev.
All Routes V_1 & V_2	56.7	70.9	72.2	71.3	71.1	67.9	48.5	84.2	67.8	10.8

Table 6.1.4-3 – Decrease Percentage of Risk Maneuvers on all routes for all vehicles

In this respect, it is obtained a global result of the risk maneuver decrease percentage of each driver on all routes (*Route 1*, *Route 2* and *Route 3*) for all vehicles (V_1 and V_2), getting a global average decrease of 67.8% with a standard deviation of 10.8%.

6.1.5. Statistical Validation

The objective of performing a statistical analysis is to ensure (verify) that the results obtained from the selected samples are representative for the rest of the drivers. In the current work, this statistical validation is carried out through hypothesis tests, in which it is proposed a null hypothesis (H_0) and an alternative hypothesis (H_1). According to the structure of this type of test, the term H_0 corresponds to the hypothesis that will be tested and the one wishes to reject, leading to the acceptance of hypothesis H_1, which usually corresponds to the question or theory that is desired to sustain. Normally, the null hypothesis H_0 is opposite to the alternative hypothesis (it is often its logical complement), and the conclusions that normally comes through these tests are two (2): one is that the rejection of H_0 is sufficient proof that H_1 is true (due to sufficient evidence of the sample data), and the other is that not being able to reject H_0 does not prove that it is true and therefore does not imply the validity of H_1 (due to insufficient evidence of the data) (Wapole et. al, 2012).

- **Efficiency Test Validation**

Taking into account the second performance test of the IDA (Section 6.1.3), the following hypothesis are established:

- Null Hypothesis (H_0): The average percentage of correct alerts is less than or equal to 90% ($\mu \leq 0.90$).
- Alternative Hypothesis (H_1): The average percentage of correct alerts is greater than 90% ($\mu > 0.90$).

According to the parameters and considerations established for this test (Sections 6.1.1 and 6.1.3), it is used one of the tails model of the *t-student* distribution to determine the veracity of H_0. Considering the hypothesis, it is decided to use the right tail of the distribution to reject the hypothesis H_0 with a confidence level of 95% ($1 - \alpha = 0.95$). Eq. 13 describes the calculation of the statistical value t_α to evaluate H_0.

$$t_\alpha = \frac{\bar{X} - \mu}{S/\sqrt{n}} \tag{13}$$

Where:

- t_α: Distribution value for a certain level of significance (α) and a certain degree of freedom ($v = n - 1$).
- $\bar{X}$: Sample mean.
- μ: Population mean.
- S: Sample standard deviation.
- n: Number of samples.

Clearing μ from the Eq. 13, it finally remains Eq. 14:

$$\mu = \bar{X} - \left(t_\alpha * S/\sqrt{n}\right) \tag{14}$$

In the current case, with 24 samples ($n = 24$), for a 95% confidence level ($\alpha = 0.05$), with 23 degrees of freedom ($v = n - 1 = 23$), it is had a value of $t_{0.05} = 1.714$. Depending on the results obtained ($\bar{X}$ y S), the value μ will be calculated and the rejection of the null hypothesis H_0 can be corroborated or not.

In the case of the statistical validation of the efficiency test, considering the exposed parameters, and replacing know the values of $\bar{X}$ and S obtained from the experimental results of the global case (Table 6.1.3-3), it is calculated the value of μ:

$$\mu = \bar{X} - \left(t_\alpha * S/\sqrt{n}\right) \tag{14}$$

$$\mu = 0.924 - \left(1.714 * 0.024/\sqrt{24}\right)$$

$$\mu = 0.924 - 0.008$$

$$\mu = 0.92 \tag{15}$$

Resulting in a $\mu > 0.9$, which implies the rejection of H_0 (null hypothesis) and therefore the veracity of H_1 (alternative hypothesis), allowing then to validate the behavior of the results for the rest of the drivers.

- **Driving Performance Test Validation**

Taking into account the third performance test of the IDA (Section 6.1.4), where it is evaluated its incidence in the driving process, the following hypothesis are established:

- Null Hypothesis (H_0): The average decrease percentage of risk maneuvers is less than or equal to 50% ($\mu \leq 0.5$).
- Alternative Hypothesis (H_1): The average decrease percentage of risk maneuvers is greater than 50% ($\mu > 0.5$).

In the same way as in the previous analysis and considering the established parameters for this test (Section 6.1.1 and 6.1.4), it is employed the right tail of the *t-student* distribution to reject the hypothesis H_0 with a confidence level of 95% ($1 - \alpha = 0.95$), and the same Eq. 14 is used to determine the value of μ with its respective statistical value t_α. In this case, with 24 samples ($n = 24$), for a 95% confidence level ($\alpha = 0.05$), with 23 degrees of freedom ($v = n - 1 = 23$), it is had a value of $t_{0.05} = 1.714$. Equally, depending on the results obtained ($\bar{X}$ y S), the value μ will be calculated and the rejection of the null hypothesis H_0 can be corroborated or not.

In the case of the statistical validation of the driving performance test, considering the exposed parameters, and replacing know the values of $\bar{X}$ and S obtained from the experimental results of the global case (Table 6.1.4-3), it is calculated the value of μ:

$$\mu = \bar{X} - \left(t_\alpha * S/\sqrt{n}\right) \tag{14}$$

$$\mu = 0.678 - \left(1.714 * 0.108/\sqrt{24}\right)$$

$$\mu = 0.678 - 0.038$$

$$\mu = 0.64 \tag{15}$$

Resulting in a $\mu > 0.5$, which implies the rejection of H_0 (null hypothesis) and therefore the veracity of H_1 (alternative hypothesis), allowing then to validate the behavior of the results for the rest of the drivers.

6.2. Analysis of Results

Based on the experimental design and the results presented in the previous section, it is now carried out an analysis of them. Following the same presentation order, first there are exposed the functionality results, followed by the efficiency ones, then the driving performance and finally the statistical validation.

6.2.1. Intelligent Driving Assistant Functionality

According to the operation samples observed in Section 6.1.2, from the point of view of functionality, the developed system complies with the established specifications and requirements. Following the reasoning of an expert driver, who supervises the driving process, the system detects and consistently alerts the risk maneuvers previously indicated in Section 5.6.

Observing the behavior of the monitored variables (SPD, LA and YAR) and according to the environment where the vehicle is located (YAR), the proposed set of fuzzy inference rules works correctly, and the developed IDA effectively adapts to the different characteristics of the environment by updating the evaluation parameters of each monitored variable. Obtaining in this way, an Intelligent Driving Assistant adaptable for multiple road scenarios.

Thanks to the support provided by the tracking window (geo-referencing) and the video record, it is possible to clarify any doubtful situation in which the user has considers or not performed a risk maneuver, and in addition, by keeping a record of the number of risk maneuvers / alerts performed by the drivers, it is possible to evaluate the driving performance of them according to the IDA criteria.

6.2.2. Intelligent Driving Assistant Efficiency

The results presented in Section 6.1.3 allow to evaluate the effectiveness degree of the assistant developed in this dissertation. In most cases, and so in the global case, it is observed a high percentage of correct alerts issued, suggesting in this way a high efficiency in the detection of risk maneuvers, and therefore, in the emission of driving assistances.

In *Route 1,* for both vehicles V_1 and V_2 (Fig. 6.1.3-1(a) and 6.1.3-3(a)), were the cases in which it is presented the lowest degree of effectiveness, obtaining a total of 77.5% and 74% for each vehicle, on the other hand, in *Route 2* (Fig. 6.1.3-1(b) and 6.1.3-3(b)) it is obtained a greater effectiveness, getting 91.6% for V_1 and 86.7% for V_2, and finally, in *Route 3* (Fig. 6.1.3-1(c) and 6.1.3-3(c)) it is obtained the highest effectiveness degree, being in this case 97.5% and 96.7% respectively (Tables 6.1.3-1 and 6.1.3-2).

This behavior of the results is due, in part, to the accident risk of each route, and mainly, to the behavior of the monitored variables from the Vehicular Telemetry System (VTS). The efficiency of the assistant is related to the number of false positives (incorrect alerts) obtained in each route, these false positives occur due to an erratic and imprecise behavior of the telemetry variables when the route passes through areas where the satellite signal is interrupted (lack of satellites in synchronization), either by wooded areas or near infrastructures such as bridges or tall buildings (elements that interfere with the GPS signal). When receiving an erroneous data, the system incorrectly interprets the maneuver and assists as if a risk maneuver was being carried out. This statement is made on the basis that most of the obtained false positives occur in these specific areas of the routes and not in a randomly way.

It is mentioned in part by the accident risk, since in routes where there is a lower accident rate, the demand of the assistant will be lower as well, and therefore the total of risk maneuvers to be detected tends to reduce, so that the few false positives present have a greater influence on the reduced number of total alerts, decreasing in this way the effectiveness percentage in these cases (*Route 1* for example). It should be noted that, this does not imply that a low accident risk directly diminishes the efficiency of the assistant, it is only an influence in the results.

However, despite these factors, finally the system presents a high degree of efficiency for both vehicles, having 93.2% for V_1 and 90.2% for V_2 in all routes

(Tables 6.1.3-1 y 6.1.3-2), and consequently a global effectiveness (for V_1 and V_2) of 92.4% (Table 6.1.3-3).

6.2.3. Driving Performance Analysis

Checking the decrease percentages of each case exposed in Section 6.1.4, it is possible to observe the incidence of using the assistant in the driving performance. In most cases, the number of risk maneuvers made by the drivers decreases after making the routes enabling IDA assistances, suggesting in this way the positive influence that the use of it has during the trips.

For both vehicles (V_1 and V_2), *Route 1* was the one with the lowest number of risk maneuvers, remaining below 10 maneuvers on average (Fig. 6.1.4-1(a) and 6.1.4-3(a)). This behavior was expected due to the "*Normal*" road accident risk (*RAR*) presented along the entire *Route 1*, by which the IDA is more permissive and then requires less care when driving compared to the other routes. However, it can also be seen the decrease percentage in the number of alerts after enabling the assistances, obtaining an average of 35% and 43.1% respectively (Tables 6.1.4-1 and 6.1.4-2).

On the other hand, *Route 2* was the one with the greatest number of alerts, staying around 60 alerts on average for V_2 and V_1 without the use of the assistances (Fig. 6.1.4-1(b) and 6.1.4-3(b)). Likewise, this behavior was also expected, in this case due to the "*High*" level of *RAR* that happens along the entire *Route 2*, by which the IDA is stricter and then requires more care when driving compared to the other routes, this even when the vehicle is on the same type of "*Urban*" road like *Route 1*. Being a road with higher accident rate, it is possible to perceive more clearly the influence of the assistant after enabling the hearing assists, decreasing to an approximate number of 20 alerts for both vehicles, and obtaining in this way an average decrease percentage of 55.9% and 73.2% in alerts for V_1 and V_2 respectively (Tables 6.1.4-1 and 6.1.4-2).

In the case of *Route 3*, the average alerts remained at just under the 60 alerts for both vehicles (Fig. 6.1.4-1(c) and 6.1.4-3(c)). Unlike the previous routes, *Route 3* has different road sections where the accident rate varies (*RAR*), having in this way roads in which the IDA behaves more strictly and others in which behaves more permissive. As in *Route 2*, the influence of the assistant is more clearly visible after enabling the assists, thus reducing the average number of maneuvers detected to approximately 14 and obtaining an average decrease of 71.6% and 67.5% for V_1 and V_2 respectively (Tables 6.1.4-1 and 6.1.4-2).

In a broader context, studying the general cases of each vehicle on all routes, it is observed that in both scenarios the average of alerts remained around 115 alerts (Fig. 6.1.4-2 and 6.1.4-4), decreasing then to an average of 36 alerts approximately after enabling the assistances. Indicating again a positive influence of the use of the assistant and obtaining a total average decrease of 65.7% for V_1 and 70.8% for V_2 (Tables 6.1.4-1 and 6.1.4-2).

Finally, and as a way of closing, Fig. 6.1.4-5 covers the average of risk maneuvers made by each driver on all routes, including both vehicles. In this case, the global average is around 230 maneuvers and is reduced to approximately 70 after enabling the assistances, obtaining a global decrease percentage of 67.8% (Table 6.1.4-3).

6.3. General Analysis

In general terms, the intelligent assistant works properly and fulfills its task of assisting the driver in real time during the driving process, this for any driver and for both type of vehicles used in the design of experiments.

It is important to highlight that, in certain occasions, it is possible to obtain false positives in the detection of risky maneuvers (incorrect alerts). This is due to an erratic behavior of the monitored variables acquired from the Vehicular Telemetry System (VTS), that by not having enough satellites in synchronization, the data supplied are erroneous and therefore the IDA incorrectly interprets the maneuver that is being carried out (e. g. a "*Soften Steering*" alert when no turning maneuver is made or a "*Brake Slowly*" alert when no acceleration/deceleration maneuver is made). This erroneous behavior in the telemetry variables also occurs when, during the travel, the route passes through wooded areas, high building areas or on cloudy days, situations in which there is some element of interference that interrupts the signal of the satellites.

Also, it must be noted the environment adaptability of the intelligent assistant, which adjust its evaluation criteria according to the type of road where the driver is and the accident risk present in said road. So that the IDA is more permissive in roads with low risk and stricter in those with high risk of accident.

Additionally, according to the IDA criteria, it is possible to study the driver's performance based on the number of risk maneuvers carried out. In this case, for most of the scenarios exposed in the experimental design, it is possible to observe a positive influence in the use of the assistant by decreasing the number of risk maneuvers performed by them. This is, of course, assuming that the driver decides to meet the assistance provided.

Chapter 7

Conclusions and Future Works

This chapter summarizes the main conclusions arisen of the analysis and discussion of the results reported in this work. The chapter also reviews the dissertation's scientific contributions and then discusses promising directions for future research and applications in certain topics in which the work of this thesis can continue. Finally, some concluding remarks are drawn.

7.1. Concluding Remarks

The work and the results exposed in Chapters 4, 5 and 6, show that it is possible to develop an "Intelligent Driving Assistant based on Accident Risk Map Analysis and Vehicle Telemetry" in real environment. The results obtained demonstrate the relevance of the design and implementation of vehicle safety systems within the framework of ITS outlined in Chapters 2 and 3.

The proposed intelligent assistant implemented by fuzzy logic, serves as an element of support for the driver during the driving process, providing suggestions on maneuvers performed for different road scenarios. Based on the information related to the vehicle motion state (VTS), to the vehicle environment (RARM) and to the supervision by video recording, it is possible to develop some adaptive evaluation criteria that allows to correctly detect risk maneuvers, this as long as there is no intervention of the satellite signal.

The performance of the system is evaluated by executing three tests. The first one consists of a functionality test, which seeks to verify the proper operation of the system, that is, corroborate that the assistant issues coherent driving alerts when the user is at risk by performing any of the previously established risk maneuvers (Section 5.6).

The second one consists of an efficiency test, which seeks to contrast the number of correct alerts against the number of total alerts issued. As can be seen in Section 6.2.2, the system achieves an efficiency above 90% of correct alerts for the selected test routes, suggesting an optimal behavior within the framework in which this work is developed.

And finally, the third test seeks to evaluate the incidence of the assistant in the performance of drivers, this contrasting the amount of risk maneuvers performed when disabling and enabling the driving assistances. As indicated in Section 6.2.3, considering the variables, factors, road scenarios and the behavior of drivers, for most of the exposed cases it is obtained a decrease in the number of risk maneuvers above 50%, noting a positive influence on the use of the assistant.

In addition, a statistical validation is carried out in order to verify that the results obtained for the selected driving samples, are equally valid for the rest of the driver population, this for a confidence level of 95%.

7.2. Main Contributions

The proposed work addresses the issue of intelligent driving assistance and contributes to the presentation of an adaptable structured approach, which allows to assist the driver based on the risk maneuvers performed during the driving process. This in real environment, for different types of roads and different types of vehicles.

The main contributions of this Thesis are described as follows:

- *Intelligent approach of a driving assistant applying soft-computing techniques, capable of emitting visual and hearing alerts using different evaluation criteria,* *data related to driving maneuvers through signals referred to vehicle movement (speed, longitudinal acceleration, Yaw angle rate), and data from a road accident risk map. The proposed intelligent assistant considers both sources of information for detecting dangerous maneuvers while driving.*

- *To the assistance process, it develops a computational tool capable of providing real-time assistance which is adaptable to different driving scenarios.*

This Thesis introduces the proposal of an Intelligent Driving Assistant (IDA) implemented by “Fuzzy Logic”, which is responsible for supplying driving recommendations in real-time, by detecting risk maneuvers through an adaptable evaluation criterion, based on the information obtained from the Vehicular Telemetry System (VTS, data related to the vehicle motion state), the Road Accident Risk Map (RARM, data related to the vehicle environment) and the video recording (Section 4.2).

- *To society, through this intelligent assistant it is expected to raise awareness and promote responsible behavior when performing the driving process.*

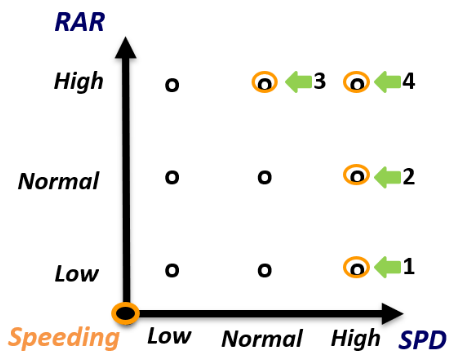
As stated in Section 3.5, so as to improve safety and comfort in the driving process, it is not enough just with the technical optimization of the vehicle, but also the optimization of the driver behavior, said in other words, driver education based on safety principles and good driving practices leads to improve the efficiency of driving assistance systems, and therefore the road safety.

7.3. Future Research and Directions

The results presented in this dissertation demonstrate the usefulness and interest in the development of intelligent driving assistants, for the enhancement of road safety. As an application in real environment, based on the analysis and observations of said results, it is possible to establish future improvements and fix future works in order to continue this line of research. So below there are exposed some topics of interest to be developed:

- One of the most important aspects to study in this work, is the elimination of false alerts. Although it was obtained a high percentage of efficiency respecting the number of correct alerts issued, there is still the possibility to eliminate entirely false positives. As in this case the false positives occur because of the inaccuracy of the data received from the VTS (due to interruption of the satellite signal by external factors), a possible countermeasure is to opt for an Inertial Navigation System as a support for the GPS signal (INS), which allows to keep track of the vehicle during those short periods of time in which the satellite signal is disabled (hardware alternative), or opt for a statistical treatment of the GPS signal (software alternative), in order to mitigate the lack of precision in those moments of time (apply a Kalman filter for example).
- On the other hand, another aspect to improve is to develop a higher resolution accident risk map, i. e., not only have the risk of accident by road section, but by sub-section or intersection, increasing in this way the adaptability of the assistant for the different road scenarios.
- Likewise, as an alternative method to study the incidence of the assistant on the driver, it is proposed to use some other assessment criteria to evaluate driving performance, different from the current criterion (number of risk maneuvers performed).
- In the same way, the application of digital image processing as a support for intelligent driving assistance (detection of drowsiness and other behaviors).
- And finally, it is proposed to explore other computational intelligence techniques, in order to develop new assessment approaches for intelligent driving assistants in the framework of ITS.

Appendix A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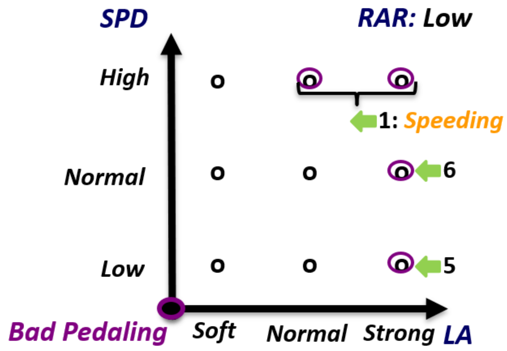
Low
3
4
2
1
Speeding
Low
Normal
High
SPD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Soft
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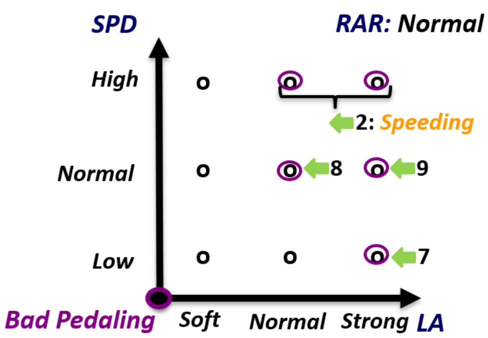
Strong
LA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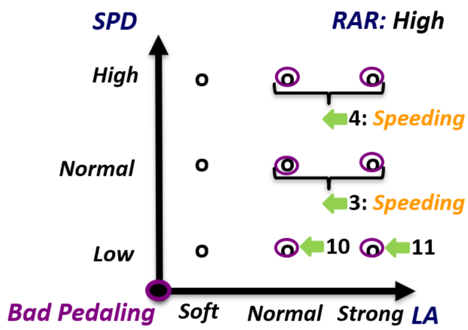
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Low
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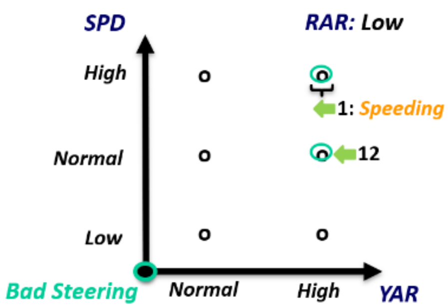
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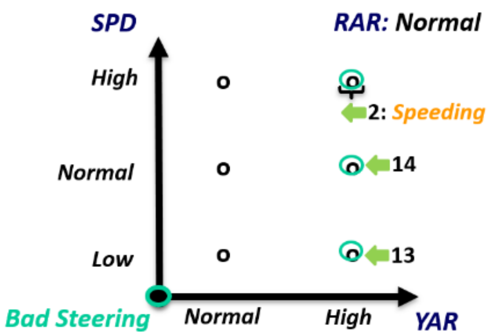
YAR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Normal
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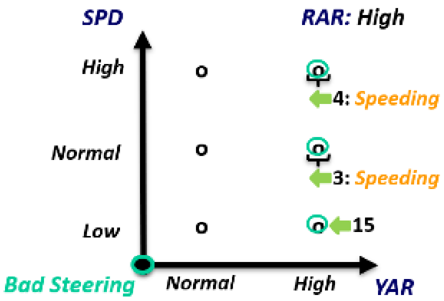
YAR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RAR: High
High
4: Speeding
Normal
3: Speeding
Low
15
Bad Steering
Normal
High
YAR

References

Alcaldía de Barranquilla Distrito Especial, Industrial y Portuario. (2012). Plan de Ordenamiento Territorial (Ley 388 de 1997) Anexo No 6: Perfiles del Sistema de Movilidad (2012). Retrieved August 29, 2017, from https://www.google.com.co/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&cad=rja&uact=8&ved=0ahUKEwiGiN2hpv3VAhVqzVQKHSBfBEgQFggkMAA&url=http%3A%2F%2Fwww.barranquilla.gov.co%2Fpublicaciones%2Fdoc_download%2F1998-anexo-no-6-perfiles-viales&usg=AFQjCNEzev6Z6LfrwCh_KSyE6LLrOwCoPw

Al-Khateeb, G. (2010). Analysis of Accident Data and Evaluation of Leading Causes for Traffic Accidents in Jordan. Jordan Journal of Civil Engineering (2010) (Vol. 4, No. 2). Retrieved October 26, 2017, from https://elearning.just.edu.jo/jjce/issues/paper.php?p=111.pdf

Bagus, G., Igi, A. & Teguh, B., A. (2017). A Review on Driver Drowsiness Based on Image, Bio-Signal, and Driver Behavior. 3rd International Conference on Science and Technology – Computer (ICST) (July 2017) (pp. 70 - 75). IEEE. doi: 10.1109/ICSTC.2017.8011855

Bounini, F., Gingras, D., Lapointe, V. & Pollart, H. (2015). Autonomous Vehicle And Real Time Road Lanes Detection And Tracking. IEEE Vehicle Power and Propulsion Conference (VPPC) (October 2015). IEEE. doi: 10.1109/VPPC.2015.7352903

Casanova, M. Leonardo. (2002). Topografía Plana (pp. 268-280). Universidad de Los Andes. Mérida, Venezuela. Retrieved January 10, 2018, from http://www.serbi.ula.ve/serbiula/libros-electronicos/Libros/topografia_plana/pdf/topografia.pdf

Cuervo, P. Andres, C. (2013). Integrated Vehicular System with Black Box Capability and Intelligent Driving Diagnosis. Universidad del Norte. Barranquilla, Colombia.

Cuervo, A., Quintero, C. & Premachandra, C. (2014). Intelligent Driving Diagnosis Based on a Fuzzy Logic Approach in a Real Environment Implementation. IEEE Intelligent Vehicles Symposium (IV) (June 2014) (pp. 102 – 107). IEEE. doi: 10.1109/IVS.2014.6856583

European Field Operational Test (euroFOT). (2012). euroFOT study demonstrates how driver assistance systems can increase safety and fuel efficiency across Europe (June 2012). Retrieved January 17, 2018, from http://www.eurofot-ip.eu/download/events/eurofot_press_release_26062012_english.pdf

European Union. (2010). On the framework for the deployment of Intelligent Transport Systems in the field of road transport and for interfaces with other modes of transport (p. 4). Retrieved October 17, 2016, from http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2010:207:0001:0013:EN:PDF

Fuchs, S., Lamprecht, B. & Bellino, M. (2007). Intelligent Driver Assistance Systems. ÖGAI Journal 25/4. Retrieved September 3, 2016, from http://vi.uni-klu.ac.at/publications/papers/2007-6.pdf

Fürer G. (2011). Driver Assistance Systems (DAS) Intelligent Accident Prevention in Road Traffic. ICT and Road Safety Forum. WISS Forum (May 19, 2011). bfu - Council for accident prevention. Retrieved September 3, 2016, from https://www.itu.int/en/ITU-T/techwatch/Documents/WSIS11-2-BFU-driver%20assistance%20systems.pdf

Gottfredson, Linda, S. (1997). Mainstream Science on Intelligence: An Editorial With 52 Signatories, History and Bibliography. University of Delaware. Retrieved January 21, 2018, from http://www1.udel.edu/educ/gottfredson/reprints/1997mainstream.pdf

Jain, C., Abhishek, R. & Pawar, R. (2014). Intelligent Driver Assistant System. International Journal of Engineering & Technology (IJERT). Retrieved October 5, 2016, from https://www.ijert.org/view-pdf/10481/intelligent-driving-assistant-system

Jiménez, F., Naranjo, J., Anaya, J., García, F., Ponz, A. & Armingol, J. (2016). Advanced Driver Assistance System for road environments to improve safety and efficiency. 6th Transport Research Arena (TRA), (April 18-21, 2016). Transport Research Procedia. Retrieved November 7, 2016, from http://ac.els-cdn.com/S2352146516302460/1-s2.0-S2352146516302460-main.pdf?_tid=e50bd3fa-a553-11e6-b89e-00000aacb360&acdnat=1478569222_f082bba0d8af11650e31ba2532e03e85

Johari, A. (2008). GSM-based notification speed detection for monitoring purposes. International Symposium on Information Technology (2008) (Vol. 4, pp. 1–7). IEEE. doi:10.1109/ITSIM.2008.4631934

Kannan, S., Thangavelu, A., & Kalivaradhan, R. (2010). An Intelligent Driver Assistance System (I-DAS) for Vehicle Safety Modelling using Ontology Approach. International Journal of UbiComp (IJU) (July 2010) (Vol. 1, No. 3). Retrieved September 3, 2016: http://airccse.org/journal/iju/papers/0710iju2.pdf

Kazuaki, G., Masaki, H., & Katsuya, M. (2012). Safe Driving Education ASSIST Education Anyware, Anytime. 9th International Conference on Ubiquitous Intelligence and Computing, 9th International Conference on Automatic and Trusted Computing (September 2012) (pp. 402 - 404). IEEE Computer Society. doi: 10.1109/UIC-ATC.2012.154

Khan, A. & Mishra, R. (2012). GPS-GSM Based Tracking System. International Journal of Engineering Trends and Technology (IJETT) (2012) (Volume 3, Issue 2, pp. 161-164). Retrieved November 6, 2016, from http://ijettjournal.org/volume-3/issue-2/IJETT-V3I2P219.pdf

Legg, S. & Hutter, M. (2007). A Collection of Definitions of Intelligence. Istituto Dalle Molle di Studi sull'Intelligenza Artificiale (IDSIA). Lugano, Switzerland. Retrieved February 4, 2018 from https://arxiv.org/pdf/0706.3639.pdf

Liu, X., Liao, S. & Rong, P. (2017). Vehicle Stability Control Based on RBF Adaptive Terminal Sliding Mode Controller. IEEE MIT Undergraduate Research Technology Conference (URTC) (November 2017) (pp. 1 – 5). IEEE. doi: 10.1109/URTC.2017.8284205

Lugano, G. (2017). Virtual Assistants and Self-Driving Cars: To what extent is Artificial Intelligence needed in Next-Generation Autonomous Vehicles? 15th International Conference on ITS Telecommunications (ITST) (May 2017). IEEE. doi: 10.1109/ITST.2017.7972192

Mehaffey, J., Yeazel, J., Penrod, S., & Deiss, A. (n.d.). NMEA data. Retrieved February 9, 2017, from http://www.gpsinformation.org/dale/nmea.htm#RMC

Mehar, A., Chandra, S. & Velmurugan, S. (2013). Speed and Acceleration Characteristics of Different Types of Vehicles on Multi-Lane Highways. European Transport \ Trasporti Europei (2013) (Issue 55, Paper No. 1). Retrieved February 10, 2018, from http://www.istiee.org/te/papers/N55/ET_2013_55_1_Mehar.pdf

Ministerio de Transporte. (2011). Decreto Número 000015 de 2011 (January 2011) (p. 2). República de Colombia. Retrieved December 9, 2017, from https://www.mintransporte.gov.co/descargar.php?idFile=5660

Minnesota Department of Transportation (MnDOT). (2004). Accident Analysis of Significant Crash Rates for Low to Very Low Volume Roadways in 10 Minnesota Counties (March 2004). Report No: MN/RC – 2004-22. Retrieved October 27, 2017, from https://www.lrrb.org/pdf/200422.pdf

National Marine Electronics Association. (2002). NMEA 0183 - Standard For Interfacing Marine Electronic Devices. Retrieved January 11, 2018, from http://www.plaisance-pratique.com/IMG/pdf/NMEA0183-2.pdf

Newell, A. (1994). Unified Theories of Cognition. Harvard University Press, 1994. Retrieved from http://books.google.com.co/books/about/Unified_Theories_of_Cognition.html?id=1lbY14DmV2cC&redir_esc=y

Pan, S. & Zhou, H. (2017). An Adaptive Fuzzy PID Control Strategy for Vehicle Yaw Stability. IEEE 2nd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC) (December 2017) (pp. 642 – 646). IEEE. doi: 10.1109/ITNEC.2017.8284810

Prajapati, N. & Bhatt, P. (2016). Driver Drowsiness Detection with Audio-Visual Warning. International Journal for Innovative Research in Science & Technology (IJIRST) (June 2016) (Volume 3, Issue 01, pp. 294 – 300). Retrieved October 14, 2016, from http://es.slideshare.net/ijirst/driver-drowsiness-detection-with-audiovisual-warning?qid=4974f5b3-c0f3-4008-86b6-e9857ba4cd59&v=&b=&from_search=29

Quintero, C. & Cuervo, A. (2017). Intelligent driving assistant based on accident risk maps analysis and intelligent driving diagnosis. IEEE Intelligent Vehicle Symposium (IV) (June 2017) (pp. 914 – 919). IEEE. doi: 10.1109/IVS.2017.7995832

RACELOGIC (2014). VBOX Mini User Guide (June 2014). Retrieved September 9, 2016, from http://www.racelogic.co.uk/_downloads/vbox/Manuals/Data_Loggers/RLVBM01_Manual.pdf

Rakhshan, A., Ray, E., & Pishro-Nik, H. (2014). Real-Time Estimation of the Distribution of Brake Response Times for an Individual Driver Using Vehicular Ad Hoc Network. Cornell University Library (April 2014). Retrieved February 2, 2018, from https://arxiv.org/abs/1405.6161

Riches, I. (2013). Automative Advanced Driver Assistance Systems Challenges and Opportunities. Strategy Analytics. Retrieved September 3, 2016, from http://on-demand.gputechconf.com/gtc/2013/presentations/S3413-Advanced-Driver-Assistance-Systems-ADAS.pdf

Ross, Timothy, J. (2010). Fuzzy Logic with Engineering Applications (WILEY Ed.) (Third Edition., p. 117). John Wiley and Sons, Ltd., Publication, 2010. Retrieved January 15, 2018 from http://iauctb.ac.ir/Files/%D9%88%D8%A8%20%D8%B3%D8%A7%DB%8C%D8%AA%20%D8%A7%D8%B3%D8%A7%D8%AA%DB%8C%D8%AF/fuzzy%20logic%20with%20engineering%20application-3rdEdition.pdf

Singh, J., Rajendra B., R. & Swetha K., S. (2015). Cost Effective Real-Time Ambulance Tracking System Prototype. International Journal of Computer Science and Information Technology Research (IJCSITR) (April – June 2015) (Vol. 3, Issue 2, pp. 58 - 61). Retrieved November 11, 2016, from file:///C:/Users/Usuario/Downloads/Cost%20Effective%20Real-Time%20Ambulance-1359.pdf

Surendra, M., Bhavana, A., Pooja, S. y Ashish, M. (2015). Eye Tracking Based Driver Drowsiness Monitoring and Warning System. International Journal of Technical Research and Applications (IJTRA) (May – June 2015) (Volume 3, Issue 3, pp. 190 - 194). Retrieved October 14, 2016, from http://es.slideshare.net/iJTRAEditor/eye-tracking-based-driver-drowsiness-monitoring-and-warning-system-62129413?qid=20774d52-a0c4-4213-9598-7d06cf0468e9&v=&b=&from_search=11

UK Department for Transport. (2010). Road Safety Research Report No. 117 The Characteristics of Speed-related Collisions. Retrieved June 6, 2016, from http://webarchive.nationalarchives.gov.uk/20120606181145/http:/assets.dft.gov.uk/publications/the-characteristics-of-speed-related-collisions/rsrr117.pdf

U.S. Department of Transportation (USDOT). (2011). Roadway Departure Safety: A Manual for Local Rural Road Owners (Appendix C). Retrieved August 28, 2017, from https://safety.fhwa.dot.gov/local_rural/training/fhwasa1109/fhwasa1109.pdf

U.S. Department of Transportation (USDOT). (2011). Roadway Safety Information Analysis: A Manual for Local Rural Road Owners (pp. 13-24). Retrieved August 24, 2017, from https://www.google.com.co/url?sa=t&rct=j&q=&esrc=s&source=web&cd=4&cad=rja&uact=8&ved=0ahUKEwimpOOW_fDVAhWESSYKHdpDBVoQFgg6MAM&url=https%3A%2F%2Fwww.hsdl.org%2F%3Fview%26did%3D4202&usg=AFQjCNG8yjbWgML0NCCr-DVIjQmE0hySag

Verband der Automobilindustrie (VDA). (2015). From Driver Assistance Systems to Automated Driving (p. 16). VDA Magazine – Automation. Retrieved September 3, 2016, from http://www.iaa.de/fileadmin/user_upload/2015/english/downloads/press/Automation-from_Driver_Assistance_Systems_to_Automated_Driving.pdf

Wapole, R., Myers, R., Myers, S. & Ye, K. (2012). Probabilidad y estadística para ingeniería y ciencias (PEARSON Ed.) (Novena Edición, pp. 561 – 564, pp. 246 – 250, pp. 319 – 324). PEARSON EDUCACIÓN, México, 2012. Retrieved March 11, 2018, from https://vereniciafunez94hotmail.files.wordpress.com/2014/08/8va-probabilidad-y-estadistica-para-ingenier-walpole_8.pdf

World Health Organization (WHO). (2015). Global status report on road safety 2015 (p. 12). Retrieved October 17, 2016, from http://www.who.int/violence_injury_prevention/road_safety_status/2015/en/

Ya-Wen, H., Jau-Woei, P. & Zong-Han, W. (2016). Design and Implementation of an Intelligent Road Detection System with Multisensor Integration. International Conference on Machine Learning and Cybernetics (ICMLC) (July 2016) (Volume 1, pp. 219 - 225). IEEE. doi: 10.1109/ICMLC.2016.7860904

Yang, Y., Luo, H., Xu, H. & Wu, F. (2016). Towards Real-Time Traffic Sign Detection and Classification. IEEE Transactions on Intelligent Transportation Systems (July 2016) (Volume 17, Issue 7, pp. 2022 – 2031). IEEE. doi: 10.1109/TITS.2015.2482461

Yay, E. & Martínez, N. (2013). SEEDrive: An Adaptive and Rule Based Driving System. 9th International Conference on Intelligent Environments (July 2013) (pp. 262 - 265). IEEE Computer Society. doi: 10.1109/IE.2013.25

Zhao, M., Käthner, D., Jipp, M., Söffker, D. & Lemmer, K. (2017). Modeling Driver Behavior at Roundabouts: Results from a Field Study. IEEE Intelligent Vehicle Symposium (IV) (June 2017) (pp. 908 – 913). IEEE. doi: 10.1109/IVS.2017.7995831